Evaluation of Techniques for Modeling the Event-Based Rainfall-Runoff Process

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Subhash Chandra

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CERTIFICATE

It is certified that the work contained in the thesis entitled "An Evaluation of Available Techniques for Event-Based Rainfall-Runoff Modeling" by Subhash Chandra (Roll No. Y210338) has been carried out under my supervision and that this work has not been submitted elsewhere for any degree.

Dr. Ashu Jain
Assistant Professor
Dept. of Civil Engineering
Indian Institute of Technology
Kanpur, India

July 15, 2004

ABSTRACT

The focus of present research work is on the modeling of the event-based rainfall-runoff (R-R) process using a variety of conventional and new techniques. Conceptual rainfall-runoff (CRR) models were used as conventional techniques and Artificial Neural Network (ANN) was used as a new techniques. Among the CRR model four widespread conceptual models, the Unit hydrograph model, Nash conceptual model, Clark conceptual model and simple non-linear Tank model, were developed. Among the ANNs, twenty different architectures having single hidden layer were explored. An attempt has also been made to develop new guidelines and methodologies for the development of the ANN models. The back propagation algorithm of MATLAB toolbox was used to develop ANN models in this study. The stream flow and rainfall data from Kentucky River Basin (KRB), USA were employed to develop all these models. The worth of multi-criteria validation for evaluating model consistency was emphasized. All models were capable to simulate runoff adequately after calibration.

Among the CRR models, UH model was found to perform best during both calibration and validation. ANN 3-10-1 was found best the ANN model when the data from many storms are combined into one training set. The evaluation results in terms of standard statistical parameters between CRR model simulation result and ANN models were found to be comparable. It was observed that rather than relying on a few performance statistics such as correlation coefficient, efficiency and root mean square error, a wide variety of error statistics including average absolute relative error, normalized mean bias error, and threshold statistics should be used to evaluate the predictive capability of the developed models. The use of such methods enables assessment of the reliability of model predictions. It also supports the further development of models by identification of weak parts and evaluation of improvements.

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I would like to express my deepest gratitude to my parents for their love, care blessings, throughout and unconditional in my whole academic career. Thanks to all people who have helped me directly or indirectly throughout the thesis work and have helped me in completing the job successfully.

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Subhash Chandra
Indian Institute of Technology
Kanpur

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Chapter 1

Introduction

1.1 General

Rapid economic and population growth, social changes, urbanization and industrialization during the last few decades have resulted in increased and diversified demand for water. Due to all these effects, water scarcity has been observed in many regions of the world, especially developing countries with arid and a semi arid climate. On the other extreme, flood losses have been soaring worldwide. Thus at the dawn of the 21st century, we find ourselves facing a formidable challenge of managing our water resources in a sustainable manner. Researchers and experts, the world over, engaged planning, development and management of water resources systems, have used many modeling tools and techniques such as Systems Analysis and Simulation, Geographical Information Systems (GIS), Artificial Neural Networks (ANN), Conceptual models, Fuzzy Logic, Decision Support Systems (DSS) and Expert Systems for modeling and management of water resources system. The continuing evolution of computer science and information technology has helped in developing more sophisticated modeling tools for tackling problems of water resources.

1.2 Statement of Problem

The focus of present research work is on the modeling of the rainfall-runoff process using a variety of conventional and new techniques. The rainfall-runoff (R-R) process is a highly nonlinear, time varying, spatially distributed, complex and dynamic process which is not easily understood and is difficult to model [*Singh, 1964*; *Kulandaiswamy and Subramanian, 1967; Chiu and Huang, 1970; Pilgrim, 1976*]. Two major approaches for modeling the R-R process are normally employed: "conceptual" (physical) modeling and "systems-theoretic" modeling (sometimes

referred to as "black box") [*Amorocho and Hart, 1964; O'Connell and Clarke, 1981; Sorooshian, 1983; Gupta, 1984; Young and Wallis, 1985; Singh, 1988; Duan, 1991*].

R-R modeling attempts to establish a link between rainfall measured over the catchment and runoff (streamflow) observed at the outlet of the catchment. The R-R models can be implemented in an operational context for many applications of hydrological engineering (e.g. water works design) and water resources management (e.g. floods or low flows forecasting, reservoir management). R-R models are tools increasingly commonly used in flood forecasting applications in an operational context and links may be made with the analyses carried out on that topic *(e.g. Burnash, 1995; Refsgaard, 1997; Tingsanchali and Gautam, 2000; Yang and Michel, 2000).*

R-R modeling can be divided into two parts, continuous modeling and event-based modeling. Continuous modeling is generally used for water supply management system; irrigation purposes, power generation, recreation, and fish and wild life propagation. Whereas event-based modeling is generally useful for flood forecasting, construction of hydraulic structure etc. This thesis is focused on event-based R-R modeling using both conceptual and systems-theoretic approach.

The conceptual rainfall-runoff (CRR) models are designed to approximate within their structures (in some physically realistic manner) the general internal sub-processes and physical mechanisms, which govern the hydrologic cycle. CRR models usually incorporate simplified forms of physical laws and are generally nonlinear, time-invariant, and deterministic, with parameters that are representative of watershed characteristics. Until recently, for practical reasons (data availability, calibration problems, etc.) most conceptual watershed models assumed lumped representations of the parameters. Conceptual watershed models are generally reported to be reliable in forecasting the most important features of the hydrograph, such as the beginning of the rising limb, the time and the height of the peak, and volume of flow. However, the implementation and calibration of such a model can typically present various difficulties requiring sophisticated mathematical tools, significant amounts of calibration data, and some degree of expertise and experience with the problem domain. While conceptual models are of importance in the understanding of

hydrologic processes, there are many practical situations, such as streamflow forecasting, where the main concern is with making accurate predictions at specific watershed locations. In such a situation, a systems-theoretic model may be preferred over a conceptual model. In the systems-theoretic approach, mathematical models are used to identify a direct mapping between the inputs and outputs without detailed consideration of the internal structure of the physical processes. In the class of systems- theoretic models, a method to predict the runoff response of the watershed on the basis of known meteorological and hydrologic time series could be based on the application of ANN. The success with which ANNs have been used to model dynamic systems in science and engineering suggests that the ANN approach may prove to be an effective and efficient way to model the R-R process in situations where explicit knowledge of the internal hydrologic sub-processes is not required. Due to this, ANNs have been proposed as efficient tools for modeling and prediction in hydrology, as black- box models *(Bishop 1994).*

There are numerous applications of ANNs for streamflow forecasting. *Kang et al.* [1993] developed ANNs for daily and hourly streamflow forecasting by selecting from among four pre-specified network structures. *Kuo-lin Hsu et al.* [1993] demonstrated the nonlinear ANN model approach to provide better representation of the rainfall-runoff relationship of the medium size Leaf River basin near Collins, Mississippi. Halff et al. (1993) designed a three-layer feed forward ANN using the observed rainfall hyetographs as inputs and hydrographs recorded by the U.S. Geological Survey (USGS) at Bellvue, Washington, as outputs. Some other examples of ANN in rainfall-runoff modeling include, Minns and Hall (1996); Shamseldin (1997); Dawson and Wilby (1998); Compo *et .al.* (1999); and Zhang and Govindaraju (2000). Most of the ANN applications above concentrate on continuous modeling of the R-R process. Jain and Indurthy (2003) modeled event-based R-R process in the Salado Creek, San Antonio, Texas using ANNs. However, that study was conducted on a small watershed using rainfall and runoff data at 5-minute time interval.

Although many ANN applications to hydrologic engineering have been reported, there are certain aspects in ANN model development for which no certain guidelines are available. Most ANN application in engineering employ back-propagation training algorithm, a trial and error method of considering different number of hidden neurons,

constant value of acceptable error for training purposes, constant value of learning rate and momentum correction factors. The back-propagation training algorithm has been reported to be inefficient in capturing complex R-R relationship and it does not guarantee the global optimum solution. The ANN models are normally developed by considering a limited number of training error statistics, which may not be able to ensure against under- and/or over-training of the network. Some of the aspects will be exposed in this study to develop definite guidelines while training of an ANN model for a particular data set.

1.3 Research Objectives

The objectives of present research effort are:

1. Evaluate the efficiency of conceptual techniques to model the event-based R-R process for large watersheds.
2. Evaluate the efficiency of ANN techniques in developing event-based R-R models for large watersheds.
3. Attempt to develop guidelines and methodologies for the proper training of the ANN models.
4. Compare the performance of various models developed using a wide variety of standard statistical performance evaluation criteria.

Many conceptual models and various architecture of ANN model will be explored. The rainfall and runoff data from the Kentucky River basin will be employed to develop all the models. A wide variety of standard statistical performance evaluation parameters will be employed to evaluate the performance of the developed models.

1.4 Organization of the Thesis

This thesis contains six chapters including this chapter. First chapter deals with brief description of the CRR models and ANN models for rainfall-runoff modeling techniques, statement of problem, objective and organization of thesis. Chapter 2 provides a brief literature review on both CRR based and ANN based R-R models. Chapter 3 presents the description of ANN. Chapter 4 describes the methodology of

models developed in this study. Chapter 5 includes the results and discussions. Finally, chapter 6 presents summary, conclusion and recommendations for future study in this area. References and appendices are provided at the end.

Chapter 2

Literature Review

2.1 General

A lot of work has been reported on rainfall-runoff modeling. Based on the problem focused in this study, the literature review has been divided into two parts: CRR models and ANN models.

2.2 CRR Models

CRR models are designed to approximate within their structures (in some physically realistic manner) the general internal sub-processes and physical mechanisms, which govern the hydrologic cycle. CRR models usually incorporate simplified forms of physical laws and are generally nonlinear, time-invariant, and deterministic, with parameters that are representative of watershed characteristics. Until recently, for practical reasons (data availability, calibration problems, etc.) conceptual watershed models assumed lumped representations of the parameters.

The unit hydrograph (UH), a method for estimating storm runoff, was first proposed by Sherman in 1932 (Chow et al. 1988), and since then has been used as a key concept. The UH was defined as the watershed response to a unit depth of excess rainfall, uniformly distributed over the entire watershed and applied at a constant rate for a given period. In 1938, after studying watersheds in the Appalachian mountains of the United States, Snyder proposed relations between some of the characteristics of the unit hydrograph, i.e. peak flow, lag time, base time, and width (in units of time) at 50% and 75% of the peak flow. Snyder's method was enhanced with the regionalization of the watershed parameters developed in 1977 by Espey, Altman and Graves. A significant contribution to the unit hydrograph theory was given by Clark (1945), who proposed a unit hydrograph which was the result of a combination of a

pure translation routing process followed by a pure storage routing process. Although Clark did not develop a spatially distributed analysis, the translation part of the routing was based on the time-area diagram of the watershed. The storage part consisted of routing the response of the translation through a single linear reservoir located at the watershed outlet. The detention time of the reservoir was selected in order to reproduce the falling limb of the observed hydrographs. Note that the actual travel time of a water particle, according to this approach, is the travel time given by the time-area diagram plus the detention time of the reservoir, which is somewhat inconsistent. Some years later, Nash (1957) proposed a unit hydrograph equation, which is a gamma distribution, i.e. the response of a cascade of identical linear reservoirs to a unit impulse. It is important to notice that the method proposed by Nash did not model the watershed itself, and was just a fitting technique based on the first and second moments of the calculated and observed hydrographs.

The 1960s brought the introduction of computers into hydrological modeling enabling complex water problems to be simulated as complete systems. The first comprehensive hydrologic computer model, the Stanford Watershed Model (SWM), was developed at Stanford University *(Crawford and Linsley, 1966)*. SWM was capable of simulating R-R process at both continuous and event basis. In the late 1960s, HEC-1 was developed by the Hydrological Engineering Center, U. S. Army Corps of Engineers to simulate surface runoff processes from precipitation and snowmelt over a watershed. Varying rainfall distributions and total storm rainfall was applied to different portions of a watershed. HEC-1 simulates surface runoff response of a river basin to precipitation by representing the basin as a system of hydrologic and hydraulic components. While such models ignore the spatially distributed, time varying, and stochastic properties of the R-R process, they attempt to incorporate realistic representations of the major nonlinearities inherent in the R-R relationships. Real-time forecasting rainfall-runoff models were developed in the late 1970s and 1980s. In 1972, the Soil Conservation Service (SCS) of the US Department of Agriculture (USDA) proposed a unit hydrograph model based on a single parameter: the lag time between the center of mass of the excess precipitation hyetograph and the peak of the unit hydrograph. The shape of the hydrograph is given by an average pre-computed dimensionless unit hydrograph curve or, as a simplification, by triangular dimensionless unit hydrograph (Chow et al. 1988). Among the more widely used and

reported lumped parameter watershed models are the Sacramento Soil Moisture Accounting (SAC-SMA) Model of the U.S. National Weather Service [*Burnash et al., 1973*].

Yet, studying the storm rainfall-runoff relation involves much more than studying the unit hydrograph. Consequently, in trying to relax the unit hydrograph assumptions of uniform and constant rainfall, and to account for spatial variability of the catchment, considerable research has been done in recent years, and many articles dealing with these topics can be found in the literature. Sugawara (1972) proposed catchment response be simulated using conceptual non-linear water tank model. He attempted to simulate the rainfall-runoff process by combining several water tanks. His model had one or two outlets on the sidewall of the water tank to simulate runoff discharge. He succeeded in predicting runoff discharge from rainfall fairly accurately. Hino and Hasebe (1984) separated the runoff discharge into three components (overland flow, subsurface flow and groundwater flow), predicted each component, and obtained good results from conceptual water tank model. Mizumura and Chiu (1985) applied the tank model to predict combined runoff of snowmelt and rainfall. They also developed this rainfall-runoff model using recession curves.

Mizumura (1995) proposed a simple water tank model to simulate the rainfall-runoff process. The model was applied to two catchments, one in Japan and other in US for predicting flood response to rainfall events. The results found from the tank model were in good agreement with the observed data.

Basha (2000) proposed a simple nonlinear conceptual model for simulating R-R phenomenon in a catchment. The model is based on the concept of a nonlinear storage outflow relationship and assumed a nonlinear loss model. The model was applied to a very small semi-arid watershed with considerable success. The proposed model can be considered as an improvement over the linear reservoir theory and an attractive and useful substitute to the linear reservoir components in more complex conceptual R-R models.

Conceptual watershed models are generally reported to be reliable in forecasting the most important features of the hydrograph, such as the beginning of the rising limb, the time and the height of the peak, and volume of flow. However, the implementation and calibration of such a model can typically present various difficulties, requiring sophisticated mathematical tools [*Sorooshian et al., 1993*], significant amounts of calibration data [*Yapo et al., 1995*], and some degree of expertise and experience with the model. Alternatively many researchers have focused their attention in the ANN technique to develop hydrologic models.

2.3 ANN Models

The use of ANN technique in water resources and streamflow prediction is relatively new. ANNs are supposed to possess the capability to reproduce the unknown relationship existing between a set of input variables (e.g., rainfall) of the system and one or more output variables (e.g., runoff) *(Chakraborty et al: 1992).* Many studies in which ANN models have been applied to problems involving runoff forecasting and weather prediction have been reported in the literature. *Kang et al.* [1993] developed ANNs for daily and hourly streamflow forecasting by selecting from among four pre-specified network structures. The neural network approach was applied to the flow prediction of the Hurm River at the Dexter sampling station, Michigan *(Karunanidhi et al, 1994).* Empirical comparisons were performed between the predictive capability of the neural network models and the most commonly used analytic nonlinear power model in terms of accuracy and convenience of use. Preliminary results were found to be quite encouraging. Markus et al. (1995) used ANNs with the back propagation algorithm to predict monthly river flows at the Del-Norte gauging Station in the Rio Grande Basin in south Colorado. The results indicated that ANNs did a good job of predicting stream flows.

Hjelmfelt and Wang (1993a–c) developed a neural network based on the unit hydrograph theory. Using linear superposition, a composite runoff hydrograph for a watershed was developed by appropriate summation of unit hydrograph ordinates and runoff excesses. Rainfall and runoff data from 24 large storm events were chosen from the Goodwater Creek watershed (12.2 km^2) in central Missouri to train and test the ANN. The resulting network was shown to reproduce the unit hydrograph better

than the one obtained through the standard gamma function representation. In a later study, Hjelmfelt and Wang (1996) compared this method with a regular three-layered ANN with back-propagation. They concluded that a regular network could not reproduce the unit hydrograph very well and was more susceptible to noise than a network whose architecture was more suited for unit hydrograph computations. In an application, using two neural networks, Zhu et al. (1994) predicted upper and lower bounds on the flood hydrograph in Butter Creek, New York. Smith, and Eli (1995) applied a back-propagation neural network model to predict peak discharge and time to peak over a hypothetical watershed. Data sets for training and validation were generated by either a linear or a nonlinear reservoir model.

Shamseldin (1997) employed neural network technique in the context of R-R modeling. The chosen form of network was tested using different types of input information. The technique was applied for four different input scenarios in each of which some or all of inputs were used. The performance of the technique was compared with those of models that utilize similar input information. The result suggested that neural network shows considerable promise in the context of R-R modeling.

Dibike and Solomatine (1998) applied ANN approach for downstream flow forecasting in the Apure river basin (Venezuela). Two types of ANN architectures, namely multi layer-perceptron (MLP) and a radial basis function (RBF) were implemented. The performances of these networks were compared with a CRR model and they were found to be slightly better for river flow forecasting problem. Tokar and Johnson (1999) employed ANN methodology to forecast daily runoff as a function of daily precipitation, temperature, and snowmelt for the Little Patuxent River Watershed in Maryland, USA. The sensitivity of the prediction accuracy to the content and length of training data was investigated. The ANN rainfall- runoff model compared favorably with results obtained using existing techniques including statistical regression and a simple conceptual model.

ASCE task committee on application of ANNs in hydrology (2000) reported that ANNs are robust tools for R-R modeling. After appropriate training, they were able to generate satisfactory results for many prediction problems in R-R modeling.

Tingsanchali & Gautam (2000) employed a neural network model with a back-propagation algorithm for flood forecasting in the tidal reach of the Chao Phraya River at Bangkok. The model developed was found to perform very well in both calibrations (training) and verification (testing). The efficiency of the forecasting model was found to be very satisfactory. Dolling and Varas (2001) employed ANN for monthly streamflow forecasting on mountain watersheds. The procedure addresses the selection of input variables, the definition of model architecture and the strategy of the learning process.

Jain and Indurthy (2003) investigated the suitability of some deterministic and statistical techniques along with the ANN technique to model an event-based rainfall-runoff process. Data derived from Salado Creek at Bitters Road, San Antonio, Texas were employed. It was found that the ANN models consistently outperformed conventional models, barring a few exceptions, and provided a better representation of an event-based rainfall-runoff process, in general. However, the duration of the rainfall considered was of the order of few minutes only, and the size of the catchment was very small.

Chapter 3

Artificial Neural Networks

3.1 General

Artificial neural networks (ANNs) are also referred to as neuro-morphic systems, parallel distributed processing, neuro-computing, natural intelligent systems and machine learning algorithms. An ANN is an information-processing paradigm that is inspired by the way biological nervous systems, such as a human brain, process the information. The key element of this paradigm is the novel structure of the information processing system. ANNs are an attempt at mimicing the patterns of the human mind. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve a specific problem. Thus, it is a mathematical model, which has a highly connected structure similar to brain cells. They consist of a number of neurons arranged in different layers, an input layer, an output layer and one or more hidden layers. The input neurons receive and process the input signals and send the output signals to other neurons in the network. The signal passing through a neuron is transformed by weights which modify the functions and thus the output signal that reaches the following neuron. Modifying the weights for all neurons in the network changes the output. Once the architecture of the network is defined, weights are calculated to represent the desired output through a learning process where the ANN is trained to obtain the expected results. ANNs, like people, learn by experience or being presented by manual examples. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Advantages of ANNs include adaptive learning, an ability to learn how to do tasks based on the data given for training or initial experience, and self-organization.

3.2 An Artificial Neuron

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the

neuron can be trained for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. The architecture of an artificial neuron is shown in Figure 3.1.

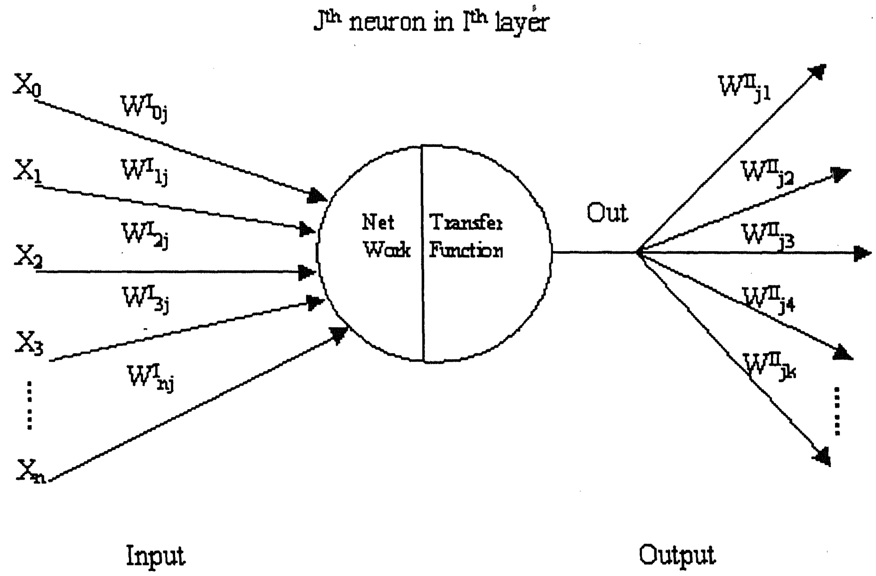


Figure 3.1: An Artificial Neuron

Note that various inputs to the network are represented by the mathematical symbol, X_n. Each of these inputs is multiplied by a connection weight, W^I_{nj}. In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output.

3.3 Architecture of ANNs

The architecture of an ANN can be of two types i.e. single-layered or multi-layered. Based on the training algorithm used to train the network, the architecture can be classified as either feed-back network or feed-forward network. Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feed-back (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straightforward networks that associate inputs with outputs. They are extensively used in pattern recognition. Feed-back networks can have signals

traveling in both directions by introducing loops in the network. Feed-back networks are very powerful and can get extremely complicated. Feed-back networks are dynamic; their state is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feed-back architectures are also referred to as interactive or recurrent.

3.4 Learning

The learning ability of an ANN is determined by its architecture and by the algorithmic chosen for training. The training method usually consists of one of three schemes:(1) unsupervised learning: The hidden neurons must find a way to organize themselves without help from the outside. In this approach, no sample outputs are provided to the network against which it can measure its predictive performance for a given vector of inputs (2) Reinforcement learning: This method works on reinforcement from the outside. The connections among the neurons in the hidden layer are randomly arranged, then reshuffled as the network is told how close it is to solving the problem. Reinforcement learning is also called supervised learning, because it requires a teacher. The teacher may be a training set of data or an observer who grades the performance of the network results. Both unsupervised and reinforcement learning suffer from relative slowness, inefficiency and reliance on a random shuffling to find the proper connection weights. (3) Back propagation: This method is proven highly successful in training of multi-layered ANNs. The network is not just given reinforcement for how it is doing on a task; information about errors is also filtered back through the system and is used to adjust the connections between the layers, thus improving performance.

3.4.1 The Back-Propagation

Back-Propagation training method is the most widely used method in engineering and scientific applications. To begin, the network is initialized; all the connection strengths are set randomly within a certain range. The network is then presented with some information. Its output is compared with known targets; the responses will initially be random. Then working backwards from the output node, each connection strength is adjusted so that next time its answer will be closer to the desired one. This whole process: input, processing, comparing output with correct answer and adjusting

connection strengths is called one 'back-propagation cycle', or often just one 'iteration'. The network is then presented with another picture and its answer is compared with the correct answer, the connection strengths adjusted where needed. This process is replaced until all training examples are exhausted. This process of training can often take hundreds or thousands of iterations. To test for this, the pictures (or whatever input is being used) should be divided into two groups: The training set, and the transfer set. The training set is used during back-propagation cycles, and the transfer set is used once learning is complete. If the network performs as well on the novel transfer stimuli as it did on the training set, then we conclude that learning has occurred.

Backpropagation is a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations of the basic algorithm. The MATLAB's Neural Network Toolbox implements a number of these variations. Properly trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The algorithm computes each EW by first computing the EA, the rate at which the error changes as the activity level of a unit is changed. For output units, the EA is simply the difference between the actual and the desired output. To compute the EA for a hidden unit in the layer just before the output layer, we first identify all the weights between that hidden unit and the output units to which it is connected. We then multiply those weights by the EAs of those output units and add the products. This sum equals the EA for the chosen hidden unit. After calculating all the EAs in the hidden layer just before the output layer, we can compute, in similar fashion, the EAs for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives back propagation its name. Once the EA has been computed for a unit, it is straightforward to compute

the EW for each incoming connection of the unit. The EW is the product of the EA and the activity through the incoming connection.

3.5 The ANN Tool Box

The MATLAB's ANN toolbox was used in this study to develop the ANN models. A brief introduction is provided here. Toolbox is simply a summary of established procedures that are known to work well. There are two features of the toolbox that are designed to improve network generalization - regularization and early stopping. To work in toolbox, first we need to go in MATLAB. A window appears as shown in Figure 3.2a.

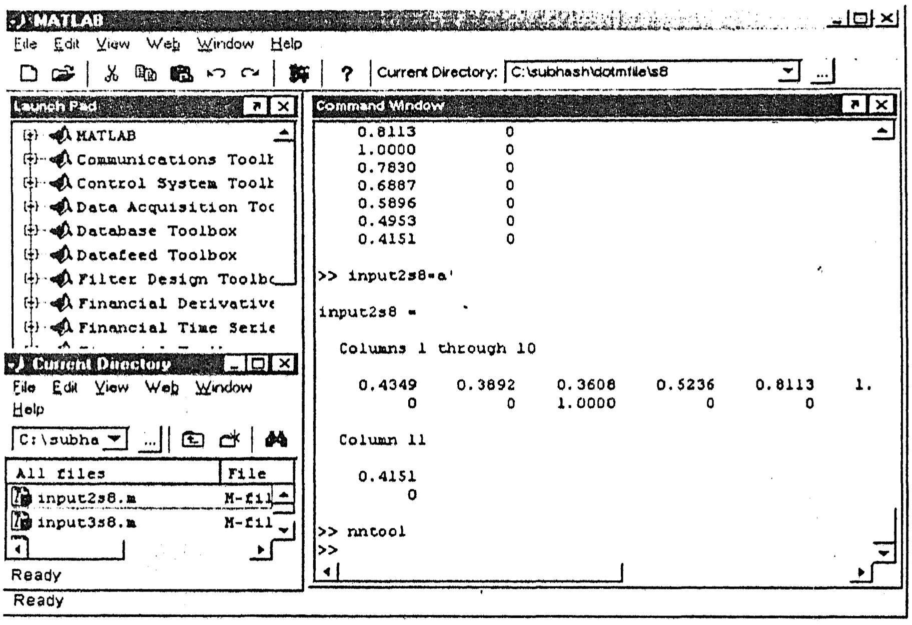


Figure 3.2a: MATLAB window

Type nntool on MATLAB prompt, a window appears (Figure 3.2b), that is neural network tool. It has different space areas such as input, target, output, error, network, input delay states, output delay states and have some operating icons. In input space area, we can give direct input or we can import data from file, similarly in target. Network can also be imported or can be created. New network window will appear as shown in Figure 3.2c. There are many types of networks available in toolbox. Feed-forward backprop, network is widely used as discussed in previous section. Input

range can be provided through input data itself or manually. This toolbox has a few training parameters that need to be specified.

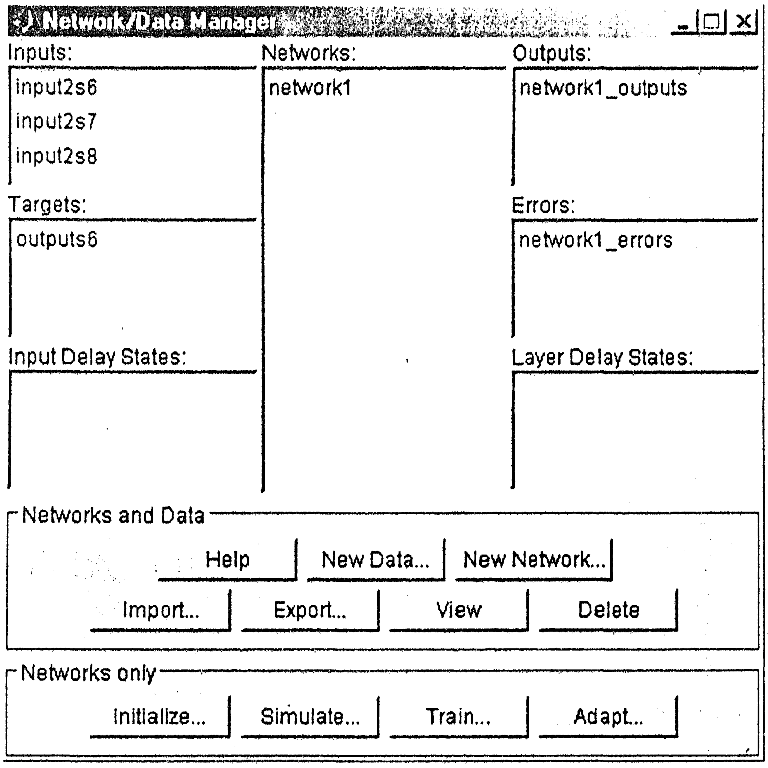


Figure 3.2b: Neural Network Tool

The Levenberg-Marquardt (TRAINLM) function is most widely used training function. It was designed to approach second-order training speed without having to compute the Hessian matrix. There are two Adaption learning functions, LEARNGDM and LEARNGD. LEARNGDM is Gradient descent with momentum weight and bias learning function, it calculates the weight change dW for a given neuron from the neuron's input P and error E, the weight (or bias) W, learning rate LR, and momentum constant MC, according to gradient descent with momentum: dW = MC*dWprev + (1-MC)*LR*gW. The previous weight change dWprev is stored and read from the learning state. LEARNGD is Gradient descent weight and bias learning function it calculates the weight change dW for a given neuron from the neuron's input P and error E, and the weight (or bias) learning rate LR, according to the gradient descent: dW = LR*gW.

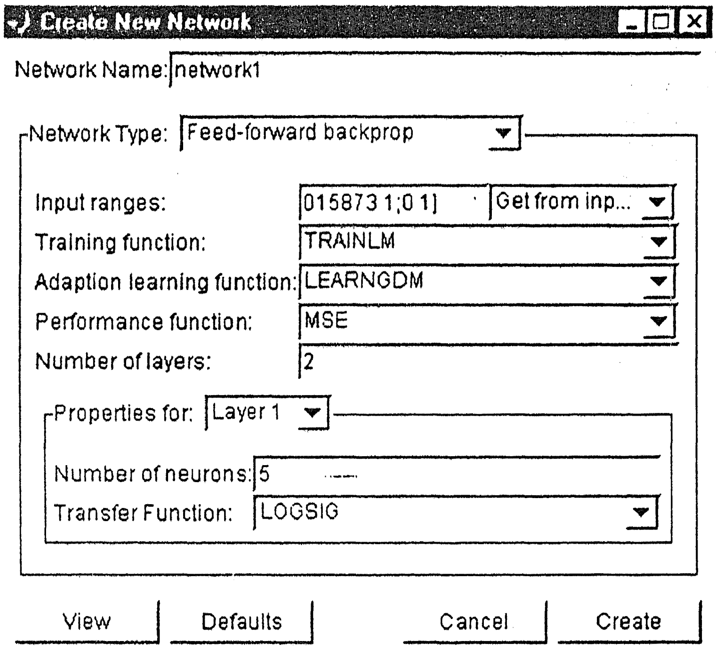


Figure 3.2c: Network type and different function

Performance function is MSE that is mean square error: It measures the network's performance according to the mean of squared errors. In addition to it, there are two more performance error, MSEREG and SSE.

Transfer Functions: There are three types of transfer functions that are available in the MATLAB toolbox. These are LOGSIG, TANSIG, and PURELIN. The function LOGSIG generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks may use the tan-sigmoid transfer function TANSIG in the applications in which input variables can range $-\infty$ to $+\infty$. Occasionally, the linear transfer function PURELIN is used in backpropagation networks. The three transfer functions are shown in Figure 3.3 a-c, respectively.

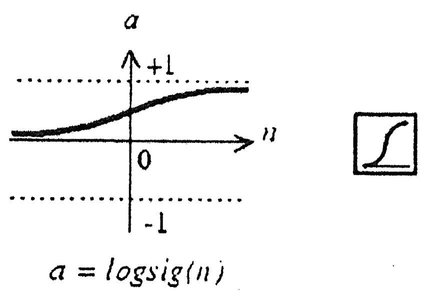


Figure 3.3a: Log sigmoid Transfer function

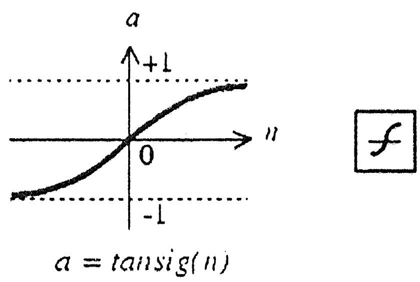


Figure 3.3b: Tan sigmoid Transfer function

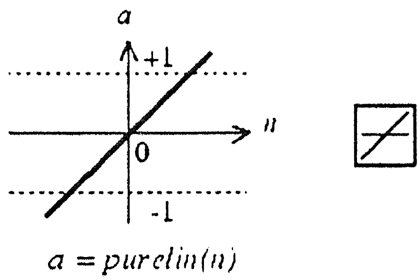


Figure 3.3c: Linear Transfer function

After adjusting all the functions when network is viewed, it appears as shown in Figure 3.4a. A plot of performance error v/s training cycle can be obtained as shown in Figure 3.4c. The trained network can be tested using testing data set.

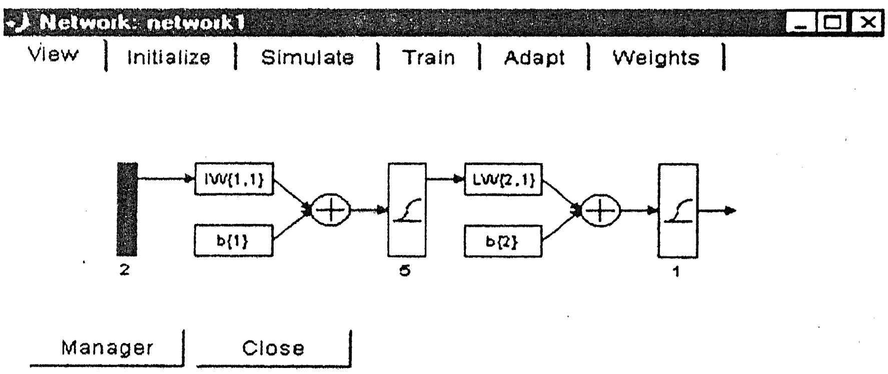


Figure 3.4a: 2-5-1 Architecture

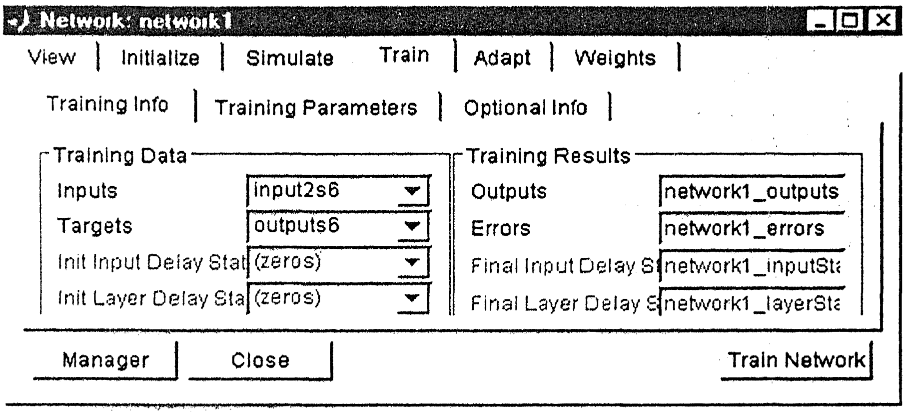


Figure 3.4b: Training Window

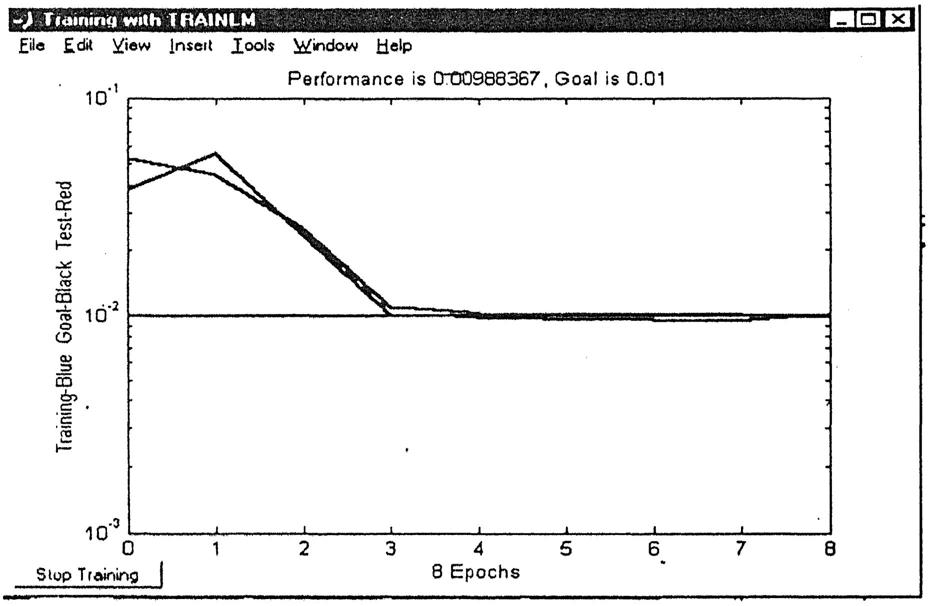


Figure 3.4c: Plot-Error v/s Training cycle

Once the ANN architecture has been trained and tested, another one can be tried. Finally, the best ANN architecture can be selected from among the various architectures investigated.

Chapter 4

Model Development

4.1 General

Two types of modeling techniques have been investigated for the purpose of modeling the event based R-R process in this study. The first type of models are conceptual models and the second type of models are ANN models. Among the conceptual category, four different models have been investigated: Unit hydrograph (UH), NASH conceptual model, Clark's conceptual model and a simple non-linear Tank model. In ANN models, many different architecture has been investigated. Stream flow and rainfall data from Kentucky River Basin, USA were employed to investigate all models structures. The performance of all the models was evaluated using six different standard statistical parameters. This chapter begins with a brief description of study area and data.

4.2 Study Area and Data

The data derived from the Kentucky River Basin were employed to calibrate/train and validate/test all CRR/ANN modes developed in this study. The Kentucky River basin is shown in Figure 4.1. Forty separate counties lie either completely or partially within the boundaries of the Kentucky River Basin. The Kentucky River is the sole water supply source for several water supply companies of the state. There is a series of fourteen Locks and Dams on the Kentucky River, which are owned and operated by the US Army Corps of Engineers. The drainage area of the Kentucky River at Lock and Dam 10 (LD 10) near Winchester is 10244 km^2. The data used in this study include average daily stream flow (cumec) (US West, 1989a), and daily (average of five stations) total rainfall (mm). The five stations are: Lexington airport, Heidelburg, Hyden, Jackson and Manchester (Figure 4.1). Out of all the data available data corresponding to 13 isolated

storms were chosen to develop all models in this study. Out of these 13 storms, data for storm 1 (S1) to storm 6 (S6) were used to calibrate/train all CRR/ANN models and the data of the remaining storms, storm 7 (S7) to 13 (S13) were used for validation/testing of all CRR/ANN models.

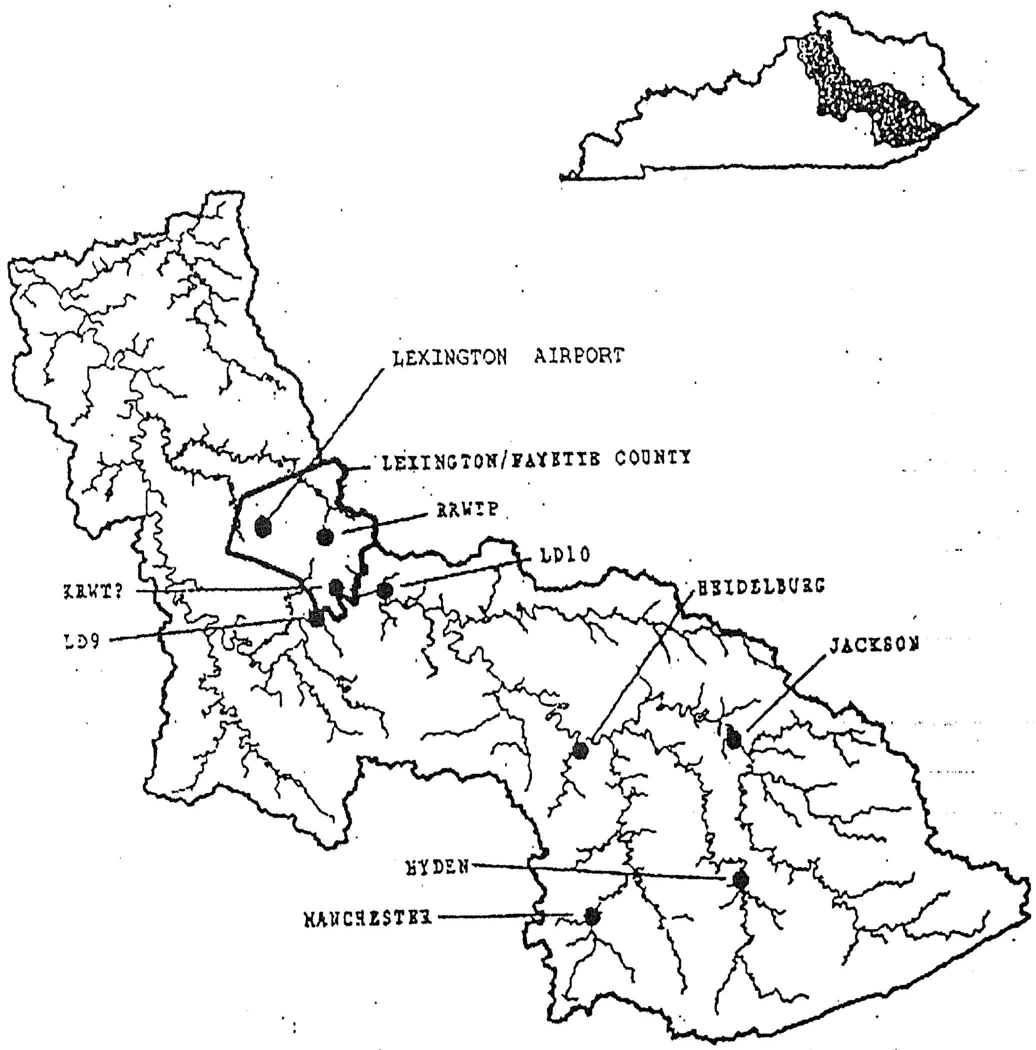
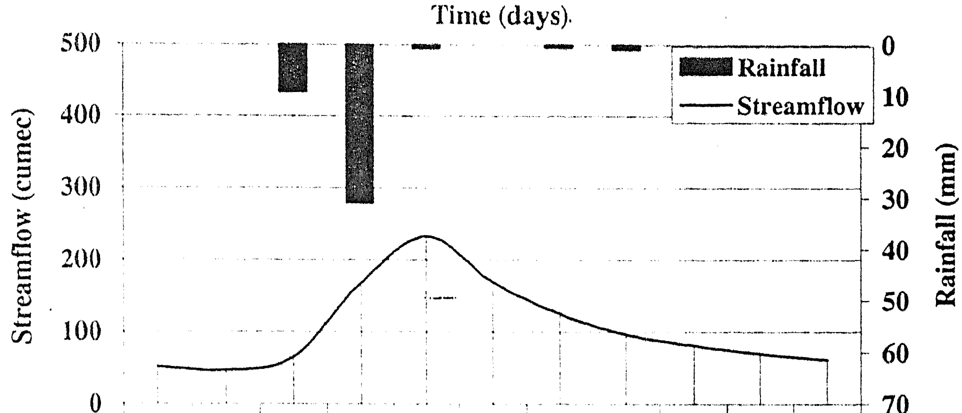


Figure 4. 1: Kentucky River Basin

LD 10 = Lock and Dam 10
KRWTP = Kentucky River Water Treatment Plant
RRWTP = Richmond Road Water Treatment Plant

These 13 storms were chosen from different years and these were having different characteristics i.e. some have low stream flow, some have medium stream flow, and

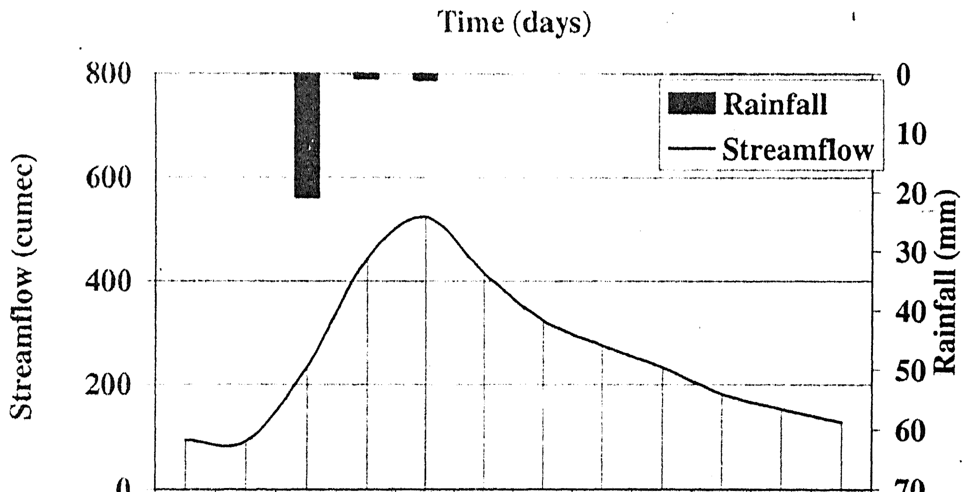
some have high stream flow. Some example storms are graphically presented in Figure 4.2 through Figure 4.5.



Day	1	2	3	4	5	6	7	8	9	10	11
Rainfall	0	0	9.2	30.8	0.6	0	0.4	0.8	0	0	0
Streamflow	51.8	47	65.3	167	233	170	126	96.7	81.5	70.2	61.8

Time (days)

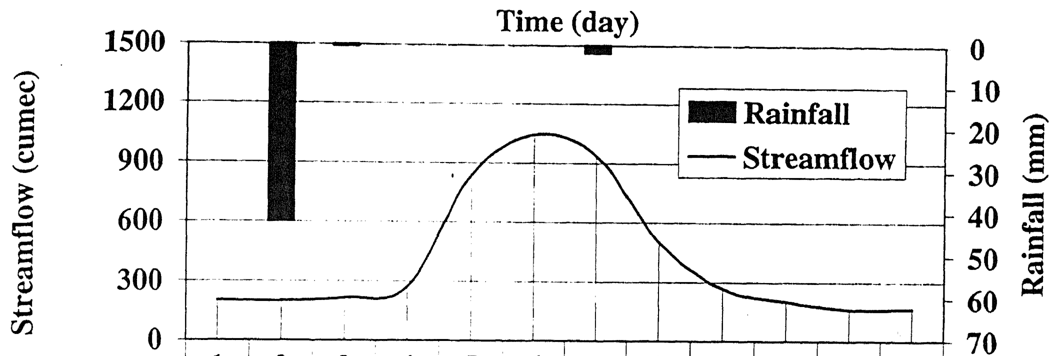
Figure 4.2: Rainfall and streamflow for the Storm S1 (May 1960)



Day	1	2	3	4	5	6	7	8	9	10	11	12
Rainfall	0	0	21	0.8	1	0	0	0	0	0	0	0
Streamflow	94	93	235	443	524	416	324	275	233	182	154	128

Time (days)

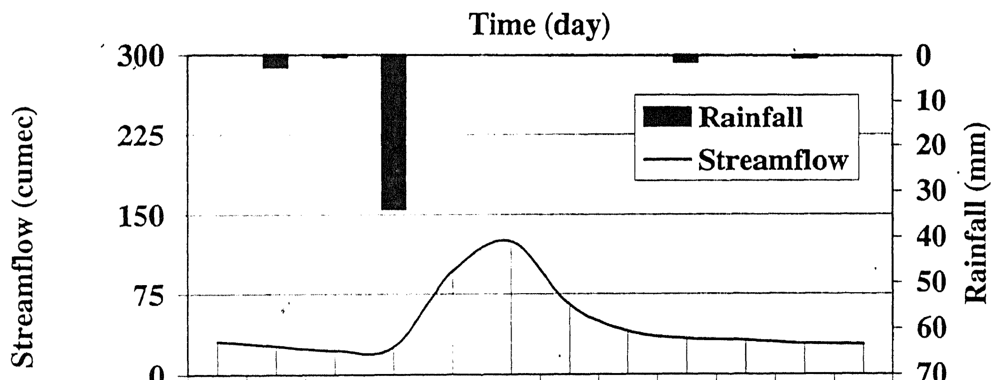
Figure 4.3: Rainfall and streamflow for the Storm S2 (May 1961)



	1	2	3	4	5	6	7	8	9	10	11	12
Rainfall	0	42	0.4	0	0	0	1.8	0	0	0	0	0
Streamflow	202	200	215	273	837	1046	937	502	268	202	162	165

Time (day)

Figure 4.4: Rainfall and streamflow for the Storm S10 (April 1970)



	1	2	3	4	5	6	7	8	9	10	11	12
Rainfall	0	2.6	0.4	34	0	0	0	0	1.4	0	0.4	0
Streamflow	31	27	23	26	97	125	65	40	33	32	29	28

Time (day)

Figure 4.5: Rainfall and streamflow for the Storm S13 (May 1972)

The model development was carried out using two different approaches in this study. The first approach used rainfall and runoff data combined from the calibration storms (S1 to S6). In the second approach the data were divided into different categories based on the peak magnitude.

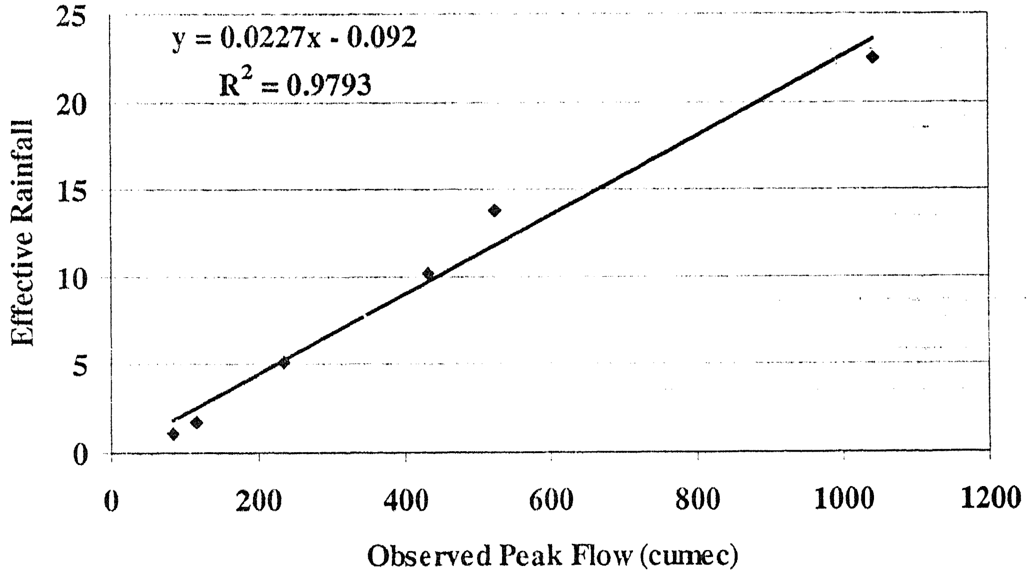


Figure 6: Relationship Between Effective Rainfall and Peak Flow from Calibration Storms

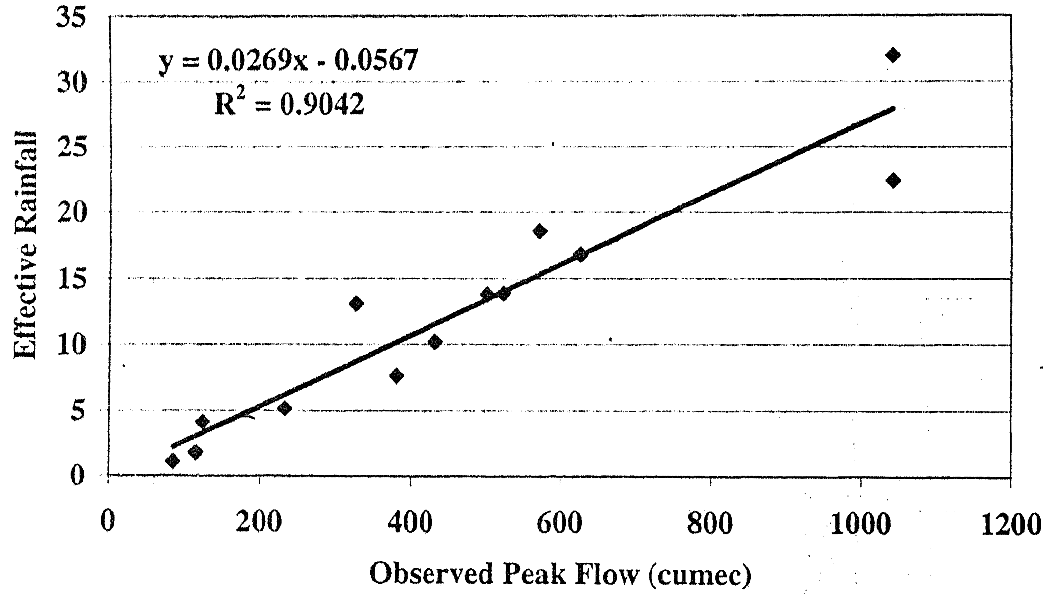


Figure 7: Relationship Between Effective Rainfall and Peak Flow from All 13 Storms

This was based on the concept that the rainfall-runoff relationships are different for different magnitude storms. In order to analyze this, the effective rainfall and flow from various storms were plotted. These plots for calibration data set and whole data set are shown in Figure 4.6 and 4.7 respectively.

Thus based on peak flow, all 13 storms were divided into 4 categories. Category-I: Storms having peak flow value between 0 to 200 cumec Category-II: Storms having peak flow value between 200 to 400 cumec Category-III: Storms having peak flow value between 400 to 600 cumec Category-IV: Storms having peak flow value between 600 to 1050 cumec. Each category consisting of at least 1 calibration/training storm and 1 validation/testing storm. For model development following procedure has been applied in this study.

4.3 Model development

The development of a mathematical model involves representing any physical system using mathematical equations that can be solved either analytically or numerically. There can be many types of models that can be tried before selecting the final one. Once a type of model is chosen, the numerical data can be used to determine the parameters of the model. This process is called calibration of the model, in ANN terminology it is also known as training. Once a model has been calibrated/trained, it needs to be validated/tested on the data it has not seen before. Then certain standard statistical performance evaluation criteria can be used to evaluate the performance of the model. This process of calibration, validation and evaluation of model performance can be carried out for different types of models. A comparison of various types of models can then be made in terms of statistical performance indices to select the best model. Finally, the selected model can be employed for forecasting and embedding in the general water-resources application. This process of model development was followed in this study and is depicted in Figure 4.8.

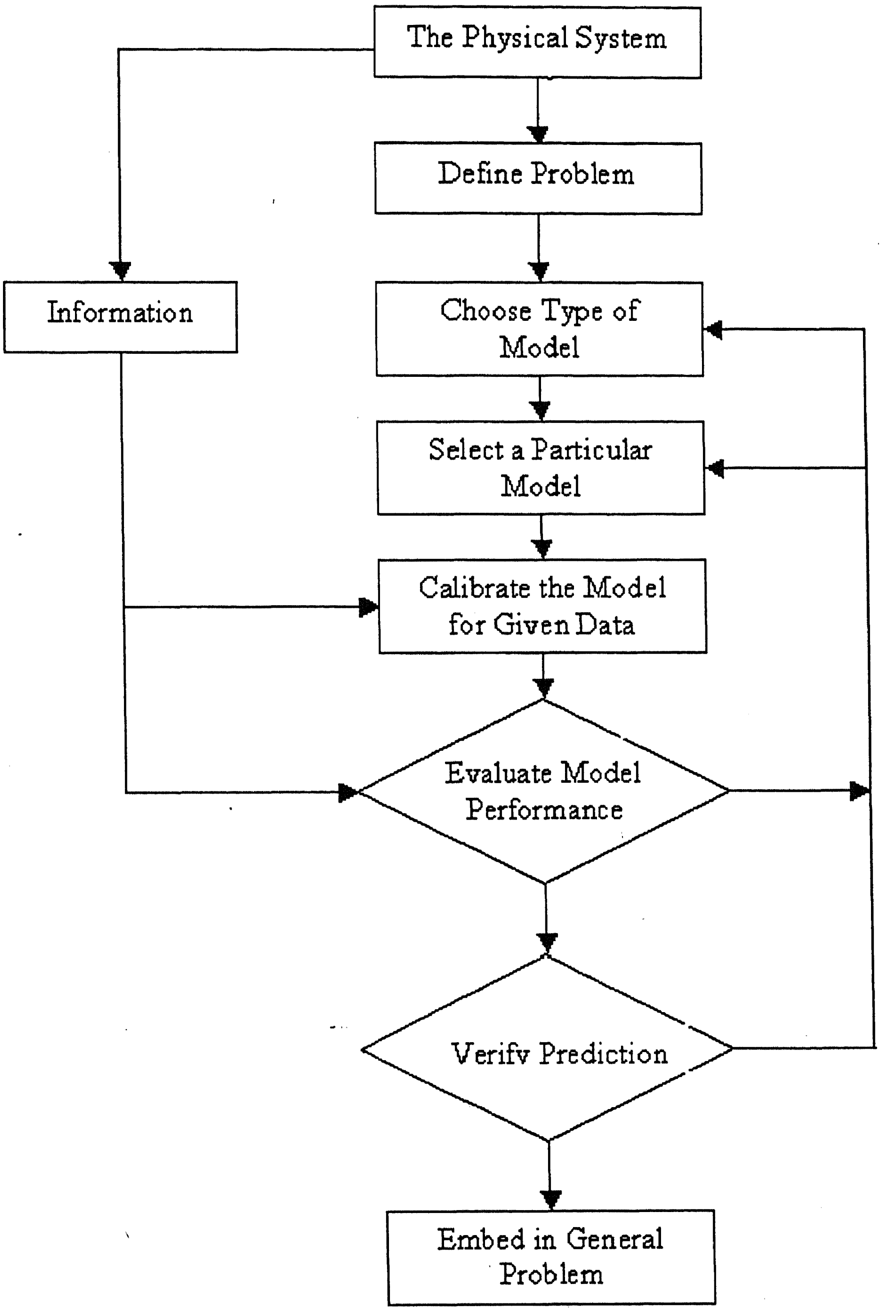


Figure 4.8: Model development procedure

Two types of models were developed in this study: conceptual models and ANN models. Among the conceptual model category four different models are being investigated: Unit hydrograph, NASH's conceptual model, Clark's conceptual model and a non-linear Tank model. Various ANN architectures were investigated before selecting the final one. The development of all the model structures investigated in this study is presented next.

4.3.1 Unit Hydrograph Model

A hydrograph is a plot of discharge v/s. time at any point of interest in a watershed, usually its outlet. Hydrographs are the measures of a watershed's response to rainfall events. The initial precipitation does not contribute directly to flow at the outlet, and instead it is stored or absorbed. This is termed the initial abstraction. Direct runoff is that portion of the precipitation that moves directly into the channel. Although several types of rainfall–runoff models are available, unit hydrograph (UH) model still remains a useful tool for flood estimation in many basins where recorded hydrological data are not sufficient to support distributed rainfall–runoff models. The UH is a powerful conceptual tool for describing rainfall-runoff relationships. This method was first suggested by Sherman in 1932 and has undergone many refinements since then.

A UH is defined as the hydrograph of direct runoff resulting from one unit depth (1 cm) of rainfall excess occurring uniformly over the basin at a uniform rate for a specified duration (D-hours). In using the deterministic UH model, one can first develop a UH using the rainfall and runoff data of an isolated rainfall event; and then use the developed UH to calculate the runoff hydrograph for another given storm having same duration. The UH of a particular duration can be converted to another UH of a different duration using either superimposition or the S-curve method, if needed. DRH is direct runoff hydrograph obtained after the base flow separation. The baseflow is delayed flow that reaches a stream essentially as groundwater flow.

A UH has three functions (Figure 4.9), input function, transfer function, and output function. Input function is nothing but the excess rainfall hyetograph. Transfer function is the UH itself and output function is the runoff hydrograph. As we apply excess rainfall on the UH, we get can direct runoff hydrograph and then depending upon topography by adding base flow, we get flow hydrograph.

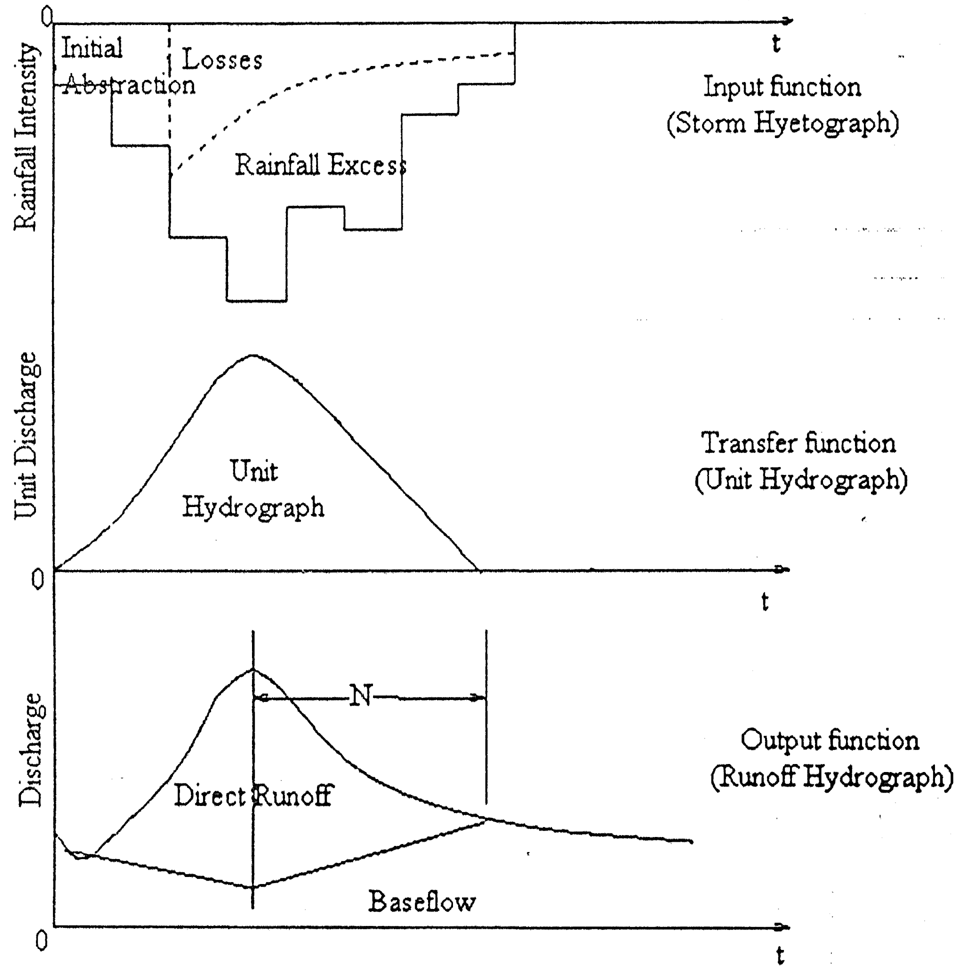


Figure 4.9: Rainfall-Runoff Process: UH Conceptual Model

In the present study the rainfall and runoff data from the 13 storms were used to investigate the UH method. The data from six storms (S1-S6) were used to develop a one-day UH. Once the six UHs were developed; they were used to predict the

validation storm. The infiltration losses were computed by using the ϕ - index method. The calculation of ϕ - index for any storm is explained next.

4.3.1.1 Calculation of ϕ - Index

The ϕ -index is the constant rate of abstractions (mm/day) that will yield an excess rainfall hyetograph (ERH) with total depth equal to direct runoff r_d over the watershed. ERH can be obtained by subtracting initial loss and infiltration losses from rainfall hyetograph (plot of rainfall intensity v/s time). The value of ϕ -index is determined by picking a time interval Δt, judging the number of interval M of rainfall that actually contribute to direct runoff, subtracting $\phi\ \Delta t$ from the observed rainfall from each intervals, and adjusting the value of ϕ and M as necessary so that the direct runoff and excess rainfall are equal:

$$r_d = \sum_{m=1}^{M} (R_m - \phi\Delta t) \tag{4.1}$$

Where, R_m is observed rainfall (mm) in time interval Δt. The values of ϕ -index for the calibration storms (S1 to S6) are presented in Table 4.1.

Table 4.1: Runoff depth and ϕ index for the calibration storms

Storm	S1	S2	S3	S4	S5	S6
Runoff-Depth (mm)	5.17	13.87	1.80	22.43	10.22	1.11
ϕ -Index (mm/day)	25.63	6.93	42.4	19.57	13.18	16.9

In order to determine the ϕ -index for the validation storms, many regression models were investigated. The regression models attempted to relate ϕ -index with explanatory variables such as base flow at the beginning of the storm (Q_g), antecedent cumulative rainfall for last 2 days (P2), 3 days (P3), 4 days (P4) and 5 days (P5). The plots of ϕ - index and these variables are shown in Figure 4.10 to Figure 4.14. It is clear that ϕ -

index shows dependence on Q_g and does not seem to be related to any of the cumulative rainfalls. A regression model of the following form was finally developed.

$$\phi = \beta_0 + \beta_1 Q_g \qquad \text{for } Q_g < 100 \text{ m}^3/\text{s} \qquad (4.2)$$

$$\phi = 10 \text{ mm/day} \qquad \text{for } Q_g > 100 \text{ m}^3/\text{s} \qquad (4.3)$$

The value of β_0 and β_1 were found to be 35.4759 and -0.2555 respectively. Regression equation and its coefficient were estimated using the regression tool in EXCEL.

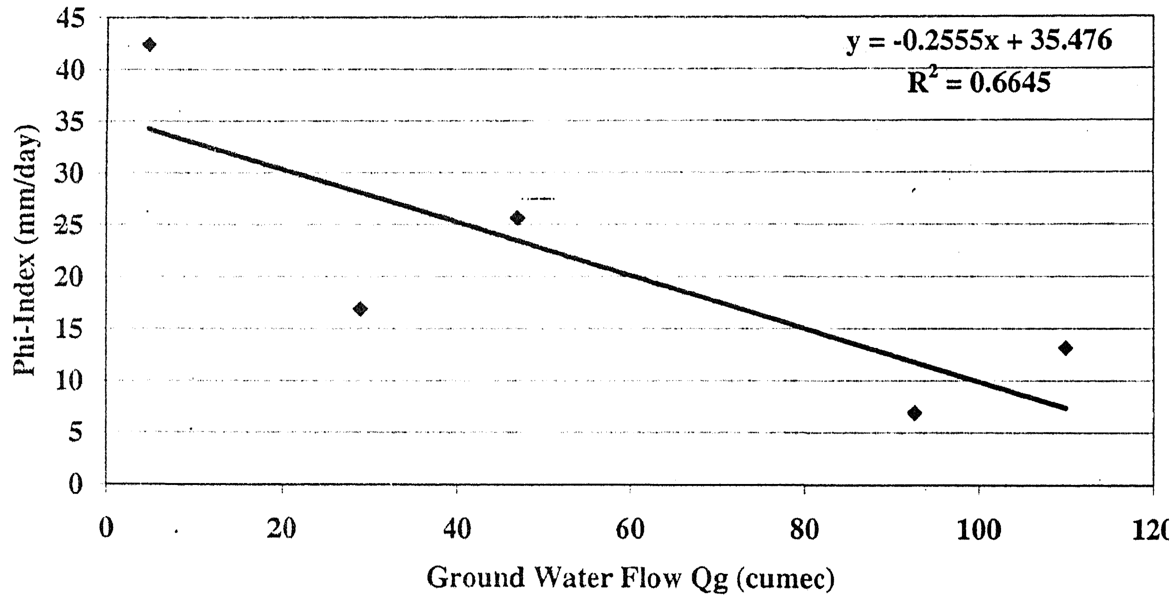


Figure 4.10: Behaviour of ϕ -Index With Ground Water Flow Magnitude

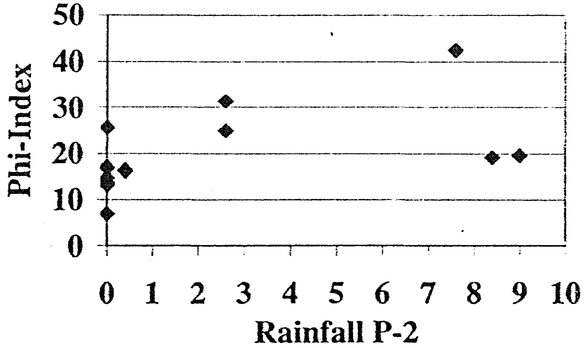


Figure 4.11: Behaviour of ϕ-Index with Total Rainfall (2-days previous)

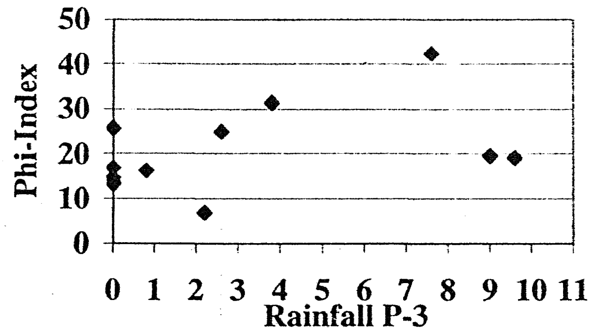


Figure 4.12: Behaviour of ϕ-Index with Total Rainfall (3-days previous)

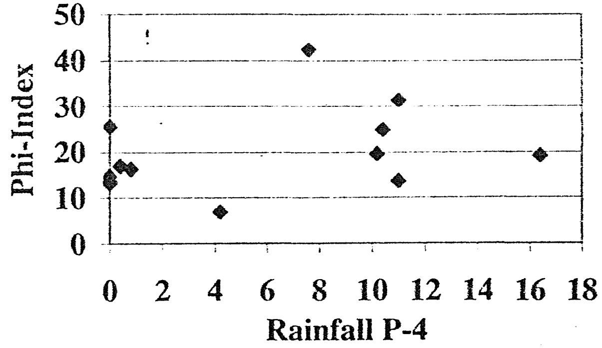


Figure 4.13: Behaviour of ϕ-Index with Total Rainfall (4-days previous)

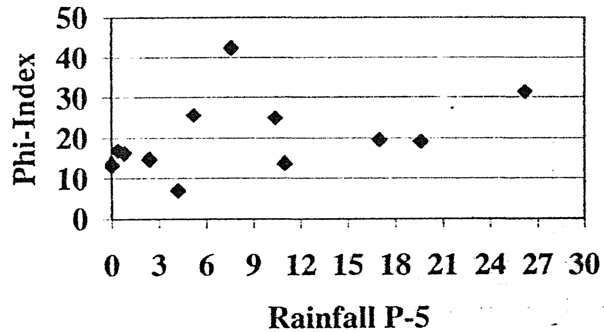


Figure 4.14: Behaviour of ϕ-Index with Total Rainfall (5-days previous)

Table 4.2: Computation of 24-hour UH by UH theory

Observed			Computed			
Time (days)	Average Rainfall (mm)	Streamflow (cumec)	ERH (mm)	Baseflow (cumec)	DRH (cumec)	24-hour UH
1	0	51.84	0	51.84	0	0
2	0	46.98	0	46.98	0	0
3	9.2	65.34	0	42.58	22.76	4.40
4	30.8	167.4	5.17	38.59	128.81	24.91
5	0.6	233.28	0	34.97	198.31	38.36
6	0	169.56	0	42.02	127.54	24.67
7	0.4	125.55	0	49.07	76.48	14.79
8	0.8	96.66	0	56.12	40.54	7.84
9	0	81.54	0	63.17	18.37	3.55
10	0	70.2	0	70.22	0	0
11	0	61.83	0	61.83	0	0

Table 4.3: Calibrated UHs from UH Model

Time (days)	UH1	UH2	UH3	UH4	UH5	UH6
0	0.00	0.00	0.00	0.00	0.00	0.00
1	4.4	10.39	6.09	2.88	4.46	3.52
2	24.91	25.51	62.19	28.32	29.86	14.95
3	38.36	31.48	30.57	37.74	36.47	55.69
4	24.67	22.32	11.12	32.92	23.06	30.02
5	14.79	14.33	5.1	13.4	13.74	10.19
6	7.84	9.46	2.59	2.82	7.64	3.77
7	3.55	5.05	1.03	0.49	3.29	0.75
8	0.00	0.00	0.00	0.00	0.00	0.00

UHs obtained using calibration storms are presented in Table 4.3 and Figure 4.15. Base flow was separated according to the Fixed Base method while developing the UHs. In the fixed base method, the surface runoff is assumed to end at fixed time or N days after the hydrograph peak. The base flow before the surface runoff began is projected ahead to the time of peak. A straight line is used to connect this projection at the peak to the point of recession limb at time N after the peak.

$$N = 0.83A^{0.2} \tag{4.4}$$

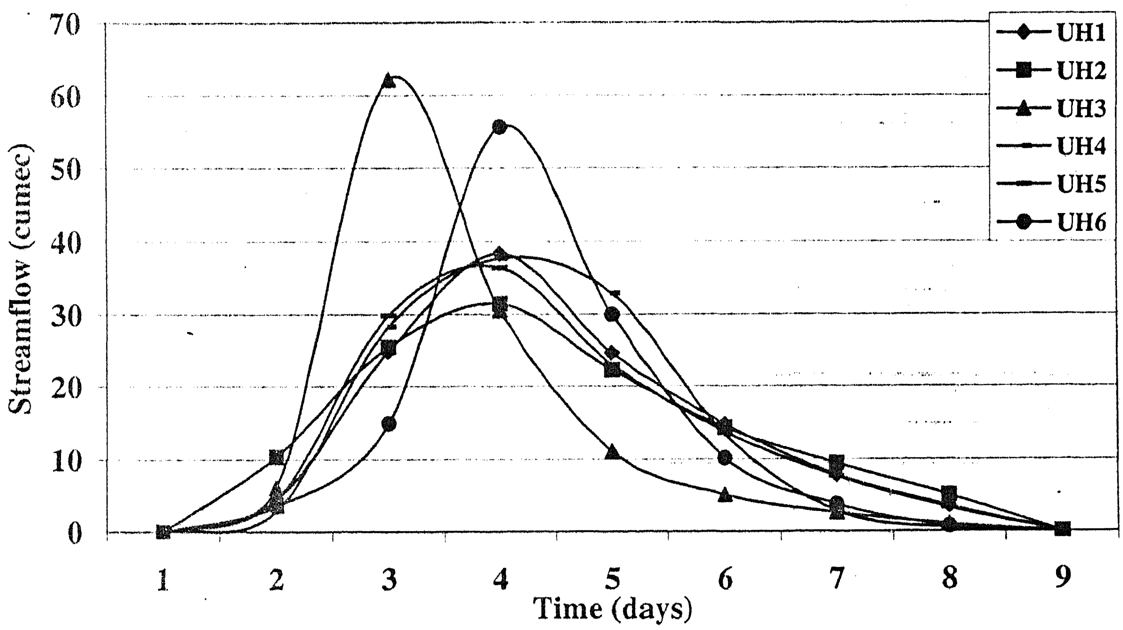


Figure 4.15: Calibrated UHs

Error statistics were computed which are discussed in next chapter

These UHs were validated using the data of the validation storms. Values of runoff depth and ϕ-indices for validation storms are shown in Table 4.4.

Table 4.4: Runoff Depth And ϕ Index For Validation Storms

Storm	S7	S8	S9	S10	S11	S12	S13
Runoff-Depth (mm)	10.21	12.33	12.89	22.87	6.66	7.90	2.40
ϕ-Index (mm/day)	13.59	16.27	14.71	19.13	24.94	13.7	31.4

The validation of the developed UHs was done using two different methods. In the first method, an average UH was computed using all six calibrated UHs. This can be accomplished by simply calculating the average of UH ordinates from UH1 to UH6 for each time step to get an average or combined UH. The ERs from validation storms were applied on average UH to compute DRH corresponding to validation storms and statistical parameters were calculated. In the second method, the 13 storms were divided into four different categories based on peak flow as mentioned earlier. Then the validation of the UH in each category was done using data from

the corresponding category in a similar fashion. The results in terms of various performance evaluation measures are presented and discussed in the next chapter.

4.3.2 NASH's Conceptual Model

The NASH conceptual model assumes the catchment to be made up of a series of n identical reservoirs each having the same storage constant (K). K is nothing but storage time constant and has the dimensions of time. It is approximately equal to the time of travel of flood wave through the channel reach. The first reservoir receives a unit volume equal to 1 cm of effective rain from the catchment instantaneously. This inflow is routed through the first reservoir to get the outflow hydrograph. The outflow from the first reservoir is considered as the input to the second; the outflow from the second reservoir is the input to the third and so on for all n reservoirs. The outflow hydrograph from the n^{th} reservoir was taken as the instantaneous unit hydrograph (IUH). An IUH is the limiting case of a UH of zero duration. Thus, it is a fictitious, conceptual unit hydrograph, which represents the surface runoff from the catchment due to an instantaneous application of the rainfall excess volume of 1 cm.

From the equation of continuity

$$I - Q = \frac{dS}{dt} \tag{4.5}$$

For a linear reservoir S = KQ; and hence

$$\frac{dS}{dt} = K\frac{dQ}{dt} \tag{4.6}$$

Substituting in equation (4.5) and rearranging

$$K\frac{dQ}{dt} + Q = 1 \tag{4.7}$$

And the solution of differential equation, where Q and I are function of time t, is

$$Q = \frac{1}{K} e^{-t/K} \int e^{t/K} I dt \tag{4.8}$$

For the first reservoir, the input is applied instantaneously. Hence for $t > 0, I = 0$. Also at $t = 0$, $\int I dt$ = instantaneous volume inflow = 1 cm of effective rain. Hence for the first reservoir equation (4.8) becomes,

$$Q_1 = \frac{1}{K} e^{-t/K} \tag{4.9}$$

For the second reservoir

$$Q_2 = \frac{1}{K} e^{-t/K} \int e^{t/K} I dt \tag{4.10}$$

Here, I = input = Q_1, thus

$$Q_2 = \frac{1}{K} e^{-t/K} \int e^{t/K} \frac{1}{K} e^{-t/K} dt = \frac{1}{K^2} t e^{-t/K} \tag{4.11}$$

Similarly, the hydrograph of outflow from the n^{th} reservoir Q_n is obtained as

$$Q_n = \frac{1}{(n-1)!} \frac{1}{K^n} t^{n-1} e^{-t/K} \tag{4.12}$$

As the outflow from the nth reservoir is caused by 1 cm on excess falling instantaneously over the catchment equation (4.12) describe the IUH of the catchment. Using the notation $u(t)$ to represent the ordinate of the IUH, equation to represent the IUH of catchment is written as

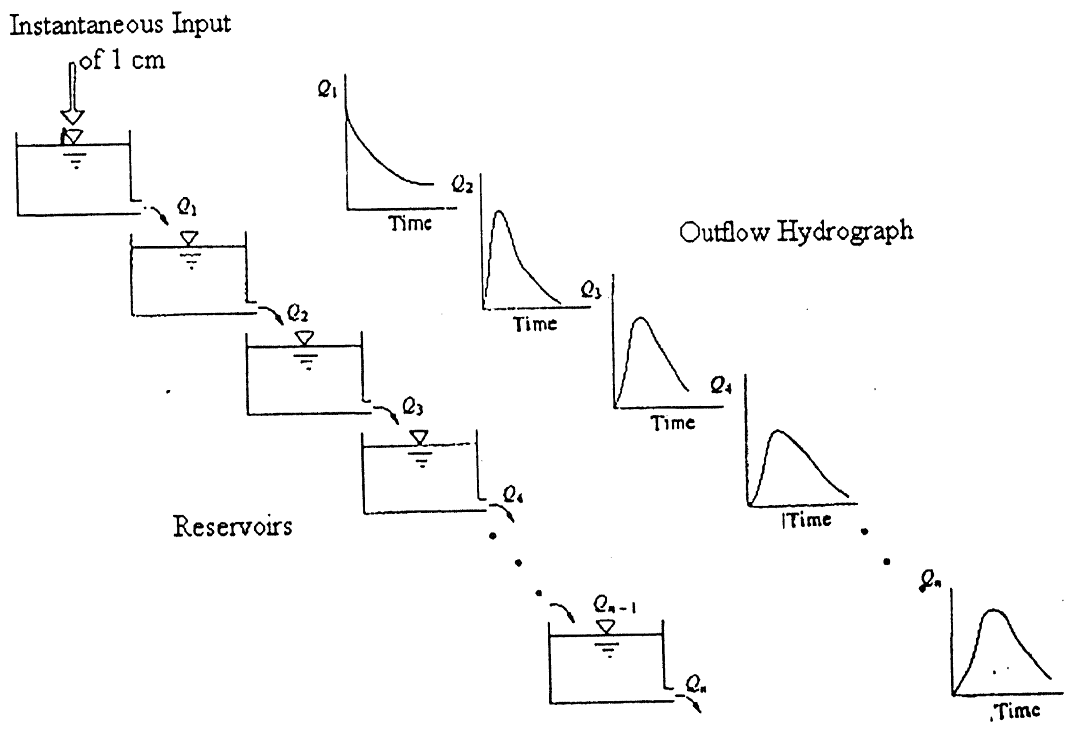


Figure 4.16: NASH Model-Cascade of n Linear Reservoirs

$$u(t) = \frac{1}{(n-1)!}\frac{1}{K^n}t^{n-1}e^{-t/K} \tag{4.13}$$

Equation (4.13) can be rewritten as

$$u(t) = \frac{1}{K\Gamma(n)}(t/K)^{n-1}e^{-t/K} \tag{4.14}$$

Here, if t is in hours, $u(t)$ will have the dimension of cm/h; K and n are constants for the catchment for to be determined by effective rainfall and flood hydrograph characteristics of the catchment. In this study for determination of n and K the moment method was applied (Subramanya, 1997). The sample calculation of n and K are shown in Table 4.5 and 4.6; and the computed value of n & K are shown in Table 4.7. These values of parameters n and K of NASH model, IUH were obtained from equation (4.14) and finally, UHs were obtained which are shown in Figure 4.17

Table 4.5: Calculation of M_{I1} and M_{I2} of Nash's Model

Time (day)	ER in Δt (mm)	Interval Δt (day)	Incremental Area	Moment Arm	First Moment	Second Moment Part (a)	Second Moment Part (b)	M_{I1}	M_{I2}
0	0	0	0	0	0	0	0	0.5	0.333
1	5.17	1	5.17	0.5	2.585	1.29	0.431		
2	0	1	0	1.5	0	0	0		
3	0	1	0	2.5	0	0	0		
4	0	1	0	3.5	0	0	0		
5	0	1	0	4.5	0	0	0		
6	0	1	0	5.5	0	0	0		
7	0	1	0	6.5	0	0	0		
8	0	1	0	7.5	0	0	0		
9	0	1	0	8.5	0	0	0		
10	0	1	0	9.5	0	0	0		
11	0	1	0	10.5	0	0	0		
		SUM=	5.17		2.585	1.2925	0.43083		

Table 4.6: Calculation of M_{Q1} and M_{Q2} of Nash's Model

Time (day)	DRH (cumec)	Average DR Rate in Δt (cumec)	Interval Δt (day)	Incremental Area	Moment Arm	First Moment	Second Moment Part (a)	Second Moment Part (b)	M_{Q1}	M_{Q2}
0	0	0	0	0	0	0	0	0		
1	22.76	11.38	1.00	11.38	0.50	5.69	2.84	0.95	3.49	14.42
2	128.81	75.78	1.00	75.78	1.50	113.67	170.56	6,32		
3	198.31	163.56	1.00	163.56	2.50	408.90	1,022.25	13.63		
4	127.54	162.92	1.00	162.92	3.50	570.23	1,995.83	13.57		
5	76.48	102.01	1.00	102.01	4.50	459.04	2,065.70	8.50		
6	40.54	58.51	1.00	58.51	5.50	321.80	1,769.93	4.87		
7	18.37	29.45	1.00	29.45	6.50	191.45	1,244.47	2.45		
8	0.00	9.18	1.00	9.18	7.50	68.88	516.65	0.76		
9	0.00	0.00	1.00	0.00	8.50	0.00	0.00	0.00		
.10	0.00	0.00	1.00	0.00	9.50	0.00	0.00	0.00		
11	0.00	0.00	1.00	0.00	10.50	0.00	0.00	0.00		
			SUM=	612.81		2139.7	8788.2	51.06		

1	M_{Q1}- M_{I1}=nK	nK= 2.99162
2	M_{Q2}- M_{I2}=nK*nK + nK*K +2*nK*M_{I1}	K= 0.71848
3	n= nK/K	n=4.16383

Table 4.7: Nash's Model Parameters- n and K

STORM	n	K (day)	ϕ-Index (mm/day)	Runoff-Depth (mm)	Time base (days)
S1	4.1638	0.7185	25.63	5.17	9
S2	3.2390	0.9106	6.93	13.87	9
S3	3.1772	0.6777	42.4	1.80	9
S4	5.2290	0.5363	19.57	22.43	9
S5	3.8818	0.7480	13.18	10.22	9
S6	6.0692	0.4711	16.9	1.11	9
Average	4.2933	0.6770	20.77	9.10	9

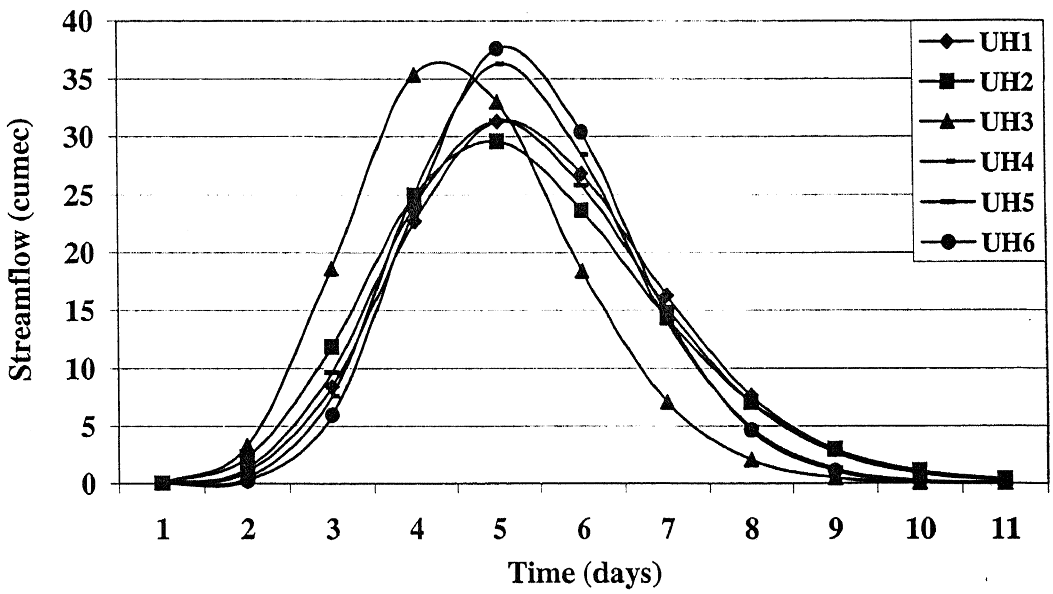


Figure 4.17: UHs for Nash model

The 24-hour UHs were developed using these IUHs. This procedure is explained in a tabular form in Table 4.9. The calculations of UHs from storms S1-S6 are presented in Table 4.8 and are shown in Figure 4.17. Once the UHs were developed using calibration storms, they were validated using the data from validation storms by computing various performance statistics, using two different methods (i.e. combines UH and category wise), as explained earlier. The result in terms of statistical parameters are presented and discussed in the next chapter.

Table 4.8: Calibrated UHs from NASH Model

Time (days)	UH1	UH2	UH3	UH4	UH5	UH6
0	0.00	0.00	0.00	0.00	0.00	0.00
1	0.01	0.05	0.03	0.00	0.01	0.00
2	1.04	2.31	3.32	0.52	1.35	0.26
3	8.43	11.89	18.63	7.63	9.66	5.99
4	22.72	24.97	35.36	25.21	24.07	23.78
5	31.30	29.59	33.02	36.32	31.34	37.63
6	26.82	23.67	18.42	28.44	25.81	30.39
7	16.28	14.34	7.09	14.04	15.27	14.56
8	7.65	7.08	2.08	4.89	7.07	4.67
9	2.95	3.00	0.50	1.30	2.72	1.10
10	0.98	1.12	0.10	0.28	0.90	0.20
11	0.29	0.38	0.02	0.05	0.27	0.03

Table 4.9: Calculation 24-hour UH from NASH Model

k=0.431 n=4.1638 Γ(n)=7.39839 Area=10244 km^2

Time (day)	*t/k*	*(t/k), n-1*	*(e, -t/k)*	*u(t)* (cm/day)	*u(t)* (cumec)	*u(t)* lagged by 24h	24-h UH (m,3/s)
0	0	0	1	0	0	0	0
1	1.39	2.85	0.25	0.13	157.84	0.00	78.92
2	2.78	25.51	0.06	0.30	351.68	157.84	254.76
3	4.18	92.01	0.02	0.27	315.36	351.68	333.52
4	5.57	228.61	0.00	0.16	194.82	315.36	255.09
5	6.96	463.13	0.00	0.08	98.12	194.82	146.47
6	8.35	824.56	0.00	0.04	43.43	98.12	70.78
7	9.74	1,342.86	0.00	0.01	17.59	43.43	30.51
8	11.13	2,048.84	0.00	0.01	6.67	17.59	12.13
9	12.53	2,974.03	0.00	0.00	2.41	6.67	4.54
10	13.92	4,150.63	0.00	0.00	0.84	2.41	1.62
11	15.31	5,611.44	0.00	0.00	0.28	0.84	0.56
12	16.70	7,389.76	0.00	0.00	0.09	0.28	0.19

4.3.3 Clark's Model

Based on an extension to time–area (TA) concept, Clark proposed a model for R-R transformation in watersheds. This method, also known as Time Area Histogram method, aims at developing IUH due to an instantaneous application of unit rainfall excess over the catchment. Time here refers to the time of concentration. The time of concentration t_c is the time required for water from the farthest point of the catchment to reach the outlet. It represents the maximum time of translation of the surface runoff of the catchment. In gauged catchments, the time of concentration can be taken as the time travel between the end of the rainfall excess and the point of inflection of the resulting surface runoff. In ungauged catchments the empirical formulae can be used to estimate t_c. The Clark's method assumes that the rainfall excess first undergoes pure translation and then attenuation. It also assumes that a linear reservoir is hypothetically available at the outlet to provide the requisite attenuation. The method uses time variable isochrones. A line joining the points having equal times of travel is called an isochrone or runoff isochrone.

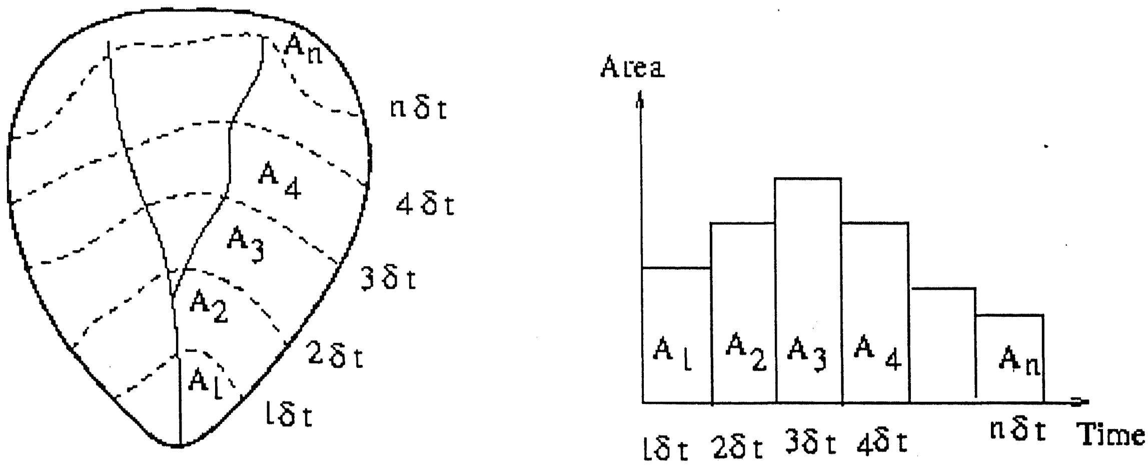


Figure 4.18(a) and (b): Isochrones and TA histogram for a watershed

The linear reservoir at the outlet, used for attenuation, can mathematically be described by equation $S = KQ$, where K is the storage time constant. The value of the K can be estimated by considering the point of inflection (P_i) of the surface runoff hydrograph. Point of inflection (P_i) is the point at which the inflow into the channel has ceased and beyond this point the flow is entirely due to withdrawal from the

channel storage. Channel storage is the volume formed by an imaginary plane parallel to the channel bottom drawn at the outflow section water surface. Continuity equation for linear reservoir is

$$I - Q = \frac{dS}{dt} \tag{4.15}$$

Beyond the point of inflection, the flow is entirely due to withdrawal from the channel storage. So continuity equation becomes

$$-Q = \frac{dS}{dt} = K\frac{dQ}{dt} \tag{4.16}$$

Hence

$$K = -Q_i/(dQ/dt)_i \tag{4.17}$$

Where suffix i refers to the point of inflection, The inflow rate I (cumec) between an inter-isochrone area (km^2) with time interval Δt_c (days) is

$$I = \frac{Area \times 10^4}{24 \times 3600 \times \Delta t_c} \tag{4.18}$$

Knowing K of the linear reservoir, the inflow at various times is routed by the Muskingum method (Subramannaya-1997) using the following equation

$$Q_2 = C_0 I_2 + C_1 I_1 + C_2 Q_1 \tag{4.19}$$

But for linear reservoir, $x = 0$; (where x is weighting factor) therefore $C_0 = C_1$ and Q_2 can be written as

$$Q_2 = 2C_1 I_1 + C_2 Q_1 \tag{4.20}$$

Where

$C_1 = (0.5\Delta t_c)/(K + 0.5\Delta t_c)$ And $C_2 = (K - 0.5\Delta t_c)/(K + 0.5\Delta t_c)$

In this study, two different Clark models were developed, Clark-1 model and Clark-2 model. In Clark-1 model, the whole catchment was considered as one area. Thus for this model, time interval (Δt_c) for inflow rate between an inter-isochrone area is equal to the time of concentration t_c. Whereas in Clark-2 model catchment was divided into two sub- areas, having A_1=3944 km^2 and A_2=6300 km^2. Clark parameters K, C_1 and C_2 were calculated for both two models. The values of K and C_1, C_2 for the catchment employed in this study are shown in Table 4.10. Using the parameters K, C_1 and C_2 of Clark-1 and Clark-2 models, IUHs were obtained. The calculation of IUH and Uh for a sample storm are shown in Table 4.11

Table 4.10: Clark's Model Parameters- C_1, C_2 and K

	Clark-1; $\Delta t_c = 2$ days			Clark-2; $\Delta t_c = 1$ day		
	K	C_1	C_2	K	C_1	C_2
Storm	(days)			(days)		
S1	2.661	0.2731	0.4537	2.661	0.1582	0.6836
S2	3.85	0.2062	0.5876	3.85	0.1149	0.7701
S3	1.058	0.486	0.028	1.058	0.321	0.358
S4	8.897	0.101	0.7979	8.897	0.0532	0.8936
S5	2.556	0.2813	0.4375	2.556	0.1636	0.6727
S6	1.944	0.3397	0.3206	1.944	0.2046	0.5908
Average	3.494	0.2812	0.4376	3.494	0.1693	0.6615

Table 4.11: Calculation of IUH and UH by Clark's Method

Time (day)	Area (km^2)	I_1 (cumec)	$2C_1I_1$ (cumec)	C_2Q_1	Ordinate of IUH (cumec)	IUH Lagged by 24 Hr	24 Hr UH (cumec)
0	0	0	0	0	0	0	0
1	3944	456.48	144.25	0.00	144.25	0.00	72.12
2	6300	729.17	230.42	98.67	329.08	144.25	236.67
3				225.09	225.09	329.08	277.09
4				153.96	153.96	225.09	189.53
5				105.31	105.31	153.96	129.64
6				72.03	72.03	105.31	88.67
7				49.27	49.27	72.03	60.65
8				33.70	33.70	49.27	41.49
9				23.05	23.05	33.70	28.38
10				15.77	15.77	23.05	19.41
11				10.78	10.78	15.77	13.28
12				7.38	7.38	10.78	9.08
13				5.05	5.05	7.38	6.21

Table 4.12: Calibrated UHs from Clark-2 Model

Time (days)	UH1	UH2	UH3	UH4	UH5	UH6
0	0.00	0.00	0.00	0.00	0.00	0.00
1	3.61	2.62	7.33	1.21	3.73	4.67
2	15.44	11.45	28.98	5.45	15.94	19.56
3	25.69	19.82	41.11	9.97	26.39	31.14
4	23.33	19.45	26.42	10.85	23.72	25.86
5	15.96	14.98	9.46	9.69	15.95	15.28
6	10.92	11.54	3.39	8.66	10.73	9.03
7	7.47	8.88	1.21	7.74	7.22	5.33
8	5.11	6.84	0.43	6.92	4.86	3.15
9	3.49	5.27	0.16	6.18	3.27	1.86
10	2.39	4.06	0.06	5.52	2.20	1.10
11	1.63	3.12	0.02	4.93	1.48	0.65

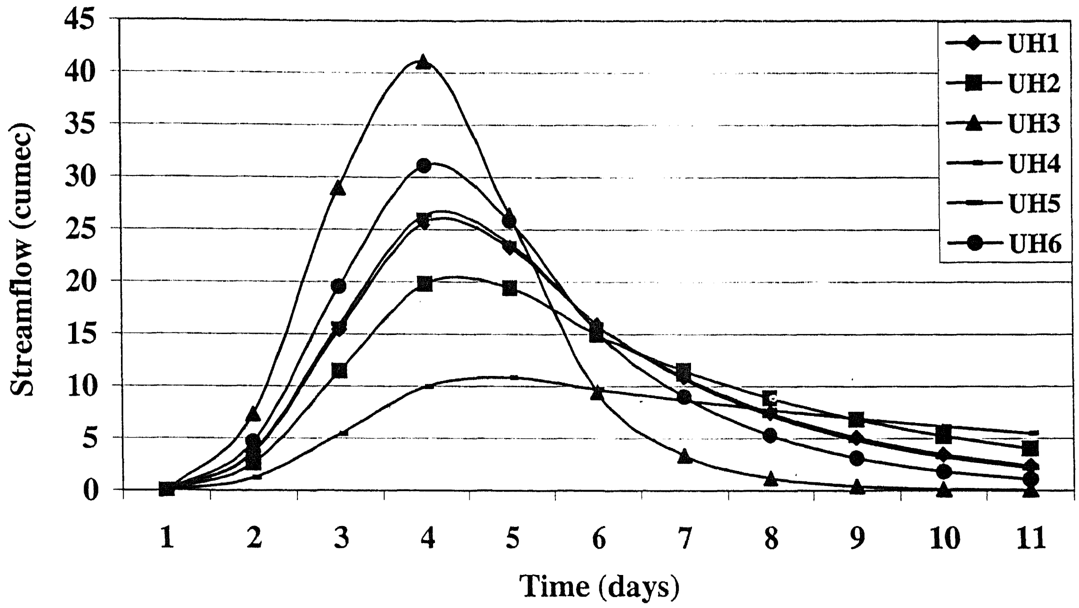


Figure 4.19: UHs for Clark-2 model

The calibrated UHs are presented in Table 4.12 and shown in Figure 4.19. Once the UHs were obtained, they were validated using the rainfall and runoff data of the validation storms using combined approach and category wise, as explained earlier. The results in terms of various performance statistics are presented and discussed in the next chapter.

4.3.4 Nonlinear Tank Model

A simple nonlinear water-tank model (due to Mizumura, 1995) was developed to simulate the rainfall-runoff process in the Kentucky River basin. Development of this model is provided in detail here. The water tank has a horizontal cross-sectional area, which is a function of the water depth and which may be determined from the recession curves of flood hydrographs. The total vertical depth of the water tank and the infiltration velocity, which governs the time lag between rainfall and runoff, are computed from the rising limbs of the flow hydrograph.

Total water depth has been divided into three components as per Mizumura Tank model, for each component the runoff discharge at time, $t + t_t$ is computed as:

$$Q' = \frac{2k_o\bar{R}\Delta t + Q(2-k_o\Delta t)}{2+k_0\Delta t}; Q \geq Q_s \tag{4.21}$$

$$Q' = \frac{2k_s\bar{R}\Delta t + Q(2-k_s\Delta t)}{2+k_s\Delta t}; Q_s \geq Q \geq Q_g \tag{4.22}$$

$$Q' = \frac{2k_g\bar{R}\Delta t + Q(2-k_g\Delta t)}{2+k_g\Delta t}; Q_g \geq Q \tag{4.23}$$

4.3.4.1 Determination of Parameters

For prediction of runoff discharge parameters k_o, k_s, k_g and Q_s, Q_g can be obtained from recession curves. The recession curves can be plotted on semi logarithmic paper. The slope of each curve can be divided into three parts. The average slope of each straight line gives mean recession coefficients k_o, k_s, k_g respectively. The two locations where slope of the straight line suddenly changes, determines the discharge parameters Q_s and Q_g. It was found that the slope of the recession curve of the ground water flow and subsurface flow components were almost constant and uniform for different floods. But the recession curves of the overland flows fluctuated. This shows that the overland flow component was produced from the different portions of the catchment during different rainfall events. The values of Tank model parameters obtained from the six storms are presented in Table 4.13.

Table 4.13: Recession Coefficient of non-linear Tank Model

STORM	S1	S2	S3	S4	S5	S6	Average
k_o=	0.1386	0.1003	0.289	0.0463	0.1434	0.1802	0.1496
k_s=	0.0957	0.0896	0.1719	0.1621	0.0887	0.1054	0.1189
k_g=	0.0551	0.0734	0.0746	0.0101	0.0507	0.0453	0.0515
Q_s=	169.56	415.8	59.4	936.9	310.5	56.16	324.72
Q_g=	70.2	182.25	8.21	210.6	137.16	21.28	104.95

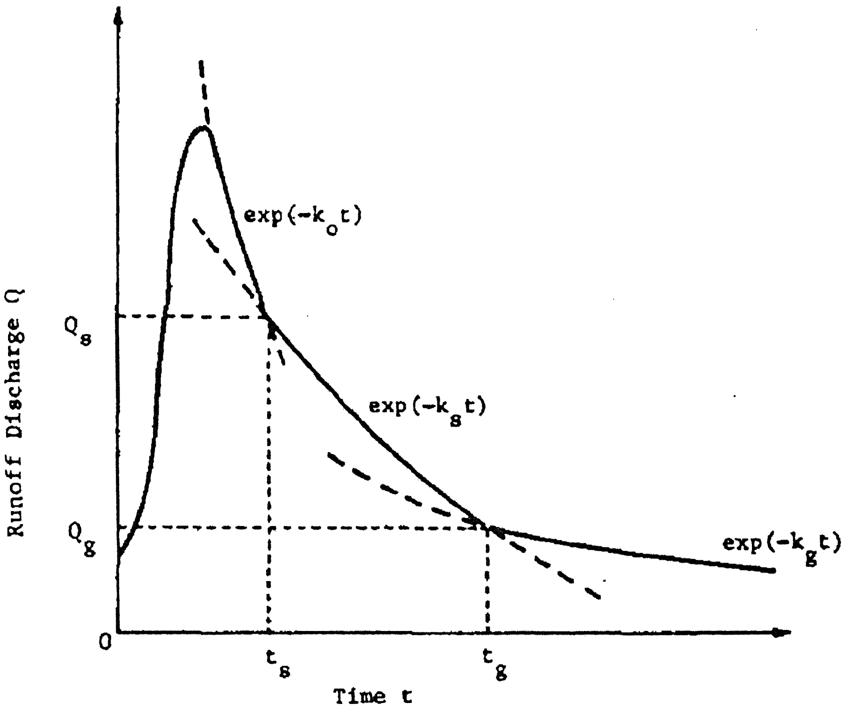


Figure 4.20 Determination of Parameters k_g, k_s, k_o, Q_g and Q_s

For the computation of runoff discharge using equations 4.21 to 4.23, the effective rainfall values first need to be calculated. Excess rainfall ($\overline{R}$) was calculated using Green-Ampt method, which is discussed next.

4.3.4.2 Calculation of Excess rainfall ($\overline{R}$)

To obtain exact analytical solution of infiltration equations, Green-Ampt proposed a more approximate physical theory. The Green-Ampt equation can be represented by the following equations:

$$F(t) - \varphi\Delta\theta \ln\left(1 + \frac{F(t)}{\varphi\Delta\theta}\right) = Kt \tag{4.24}$$

$$f(t) = K\left(1 + \frac{\varphi\Delta\theta}{F(t)}\right) \tag{4.25}$$

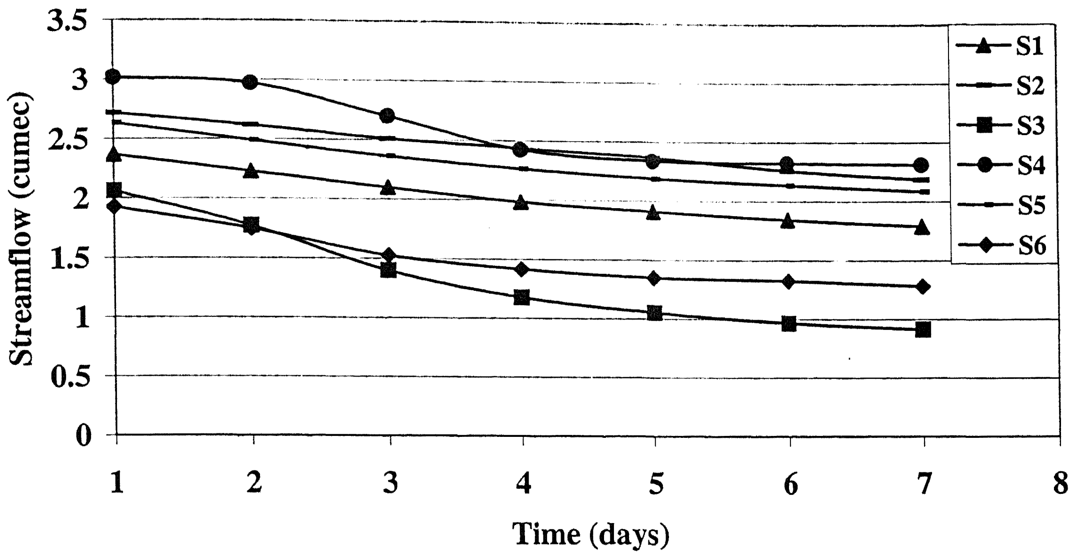


Figure 4.21: Schematic Plot of Recession Curves on Semi logarithmic Graph

Green-Ampt parameters were taken from an existing study on the same catchment. Using these equation and parameters, infiltration at each time step during the storm can be calculated. Once the infiltration has been obtained, effective rainfall at each time step can be computed. The values of effective rainfall from all 13 storms are presented in Table A-11 in Appendix. Knowing the parameters of the Tank model and effective rainfall at different time-steps, equations 4.21 to 4.23 were used to compute the runoff response of the watershed for different storms. The runoff was computed for both calibration and validation storms using the two different approaches (combined and category wise) as explained earlier. A sample calculation of computation of flow hydrograph by Tank model is shown in Table 4.14. The results in terms of performance statistics are presented and discussed in the next chapter.

Table 4.14: Calculation of Flow Hydrograph by Tank model

k_g= 0.05514; k_o= 0.13855; k_s= 0.09575 per day; Q_s= 169.56; Q_g= 70.2 cumec

Time day	Hydrograph (cumec)	ER	$2k_gR^*\Delta t$	$Q(2-k_g^*\Delta t)$	$2+k_g^*\Delta t$	Q_g	$2k_sR^*\Delta t$	$Q(2-k_s^*\Delta t)$
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	51.84	0.00	0.00	0.00	2.06	0.59	0.00	0.00
2	46.98	0.00	0.00	1.15	2.06	0.56	0.00	0.00
3	65.34	0.00	0.00	1.09	2.06	0.53	0.00	0.00
4	167.40	5.71	0.63	1.03	2.06	0.81	1.09	0.00
5	233.28	0.00	0.00	1.57	2.06	0.76	0.00	0.99
6	169.56	0.00	0.00	1.49	2.06	0.72	0.00	0.90
7	125.55	0.00	0.00	1.41	2.06	0.68	0.00	0.82
8	96.66	0.00	0.00	1.33	2.06	0.65	0.00	0.75
9	81.54	0.00	0.00	1.26	2.06	0.61	0.00	0.68
10	70.20	0.00	0.00	1.19	2.06	0.58	0.00	0.62
11	61.83	0.00	0.00	1.13	2.06	0.55	0.00	0.00

$2+k_s^*\Delta t$	Q_s	$2k_oR^*\Delta t$	$Q(2-k_o^*\Delta t)$	$2+k_o^*\Delta t$	Q_o	$Q_o+Q_s+Q_g$	(cumec)	Computed
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2.10	0.00	0.00	0.00	2.14	0.00	0.59	70.20	70.20
2.10	0.00	0.00	0.00	2.14	0.00	0.56	66.43	66.43
2.10	0.00	0.00	0.00	2.14	0.00	0.53	62.87	62.87
2.10	0.52	1.58	0.00	2.14	0.00	1.33	157.68	157.68
2.10	0.47	0.00	0.00	2.14	0.00	1.24	146.89	146.89
2.10	0.43	0.00	0.00	2.14	0.00	1.15	136.89	136.89
2.10	0.39	0.00	0.00	2.14	0.00	1.08	127.62	127.62
2.10	0.36	0.00	0.00	2.14	0.00	1.00	119.02	119.02
2.10	0.32	0.00	0.00	2.14	0.00	0.94	111.04	111.04
2.10	0.00	0.00	0.00	2.14	0.00	0.58	68.83	68.83
2.10	0.00	0.00	0.00	2.14	0.00	0.55	65.13	65.13

4.3.5 ANN Model

The main task in developing an ANN model is the selection of the optimal architecture. An optimal architecture may be considered as the one yielding the best performance in terms of error minimization, while retaining a simple and compact ANN structure. A trial and error procedure is generally applied to decide on the optimal architecture. The first step in the development of an ANN model is the selection of input and output variables.

4.3.5.1 Selection of Input and Outputs

The development of an ANN model involves the selection of the number of input and hidden neurons. The identification of input and output neurons can be determined using trial and error procedure. In present study, ANN architecture of single hidden layer was employed. The output layer consists of a single neuron representing the flow to be modelled $Q(t)$. The neurons were selected based on the auto-correlation analysis of the flow data. In a rainfall-runoff modeling, the inputs are normally present and past rainfalls and past flow values. The results of auto-correlation are presented in Table 4.15 and Figure 4.22. It is clear from these results that the flow value for lag one only is significant in modeling $Q(t)$.

Table 4.15: Auto-correlation coefficients

Lag	S1	S2	S3	S4	S5	S6
(day)	ACC	ACC	ACC	ACC	ACC	ACC
0	1	1	1	1	1	1
1	0.6243	0.6525	0.327	0.6622	0.5958	0.5179
2	0.0017	0.0388	-0.1445	0.0599	-0.0319	-0.0548
3	-0.422	-0.3945	-0.3014	-0.4433	-0.4987	-0.3583
4	-0.5043	-0.4884	-0.1912	-0.5485	-0.4331	-0.4337
5	-0.3603	-0.3958	-0.1463	-0.406	-0.3341	-0.3017
6	-0.2009	-0.2627	-0.1328	-0.1535	-0.2101	-0.1561
7	0.0212	-0.0552	-0.0773	0.0387	-0.0103	-0.0594
8	0.1466	0.1285	0.0734	0.1386	0.1496	0.1058

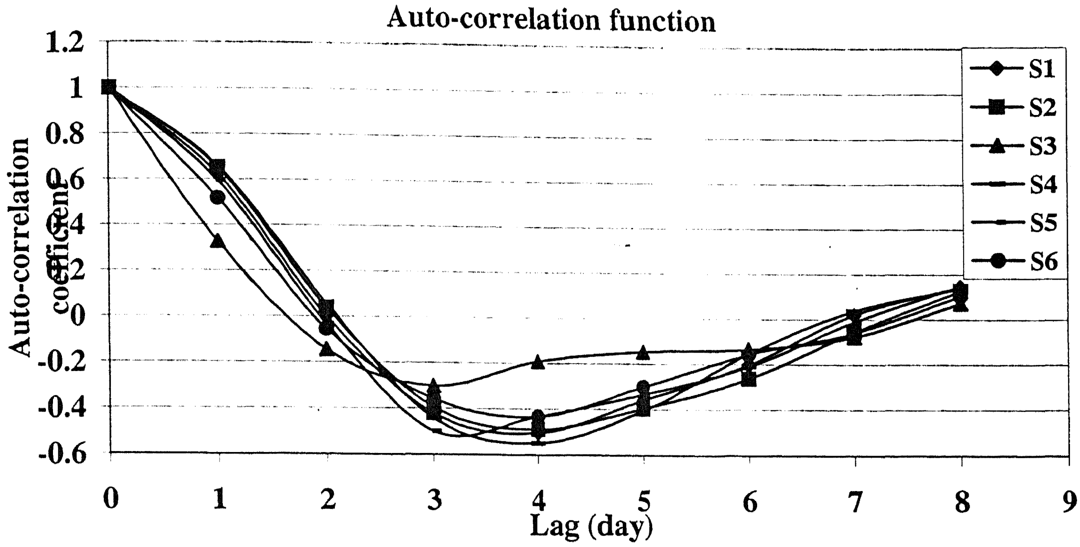


Figure 4.22: Auto-correlation function v/s Lag

The other input variable in the ANN models were effective rainfalls at two consecutive time steps i.e. *R(t)* and *R(t-1)*. Two different types of ANN models were developed in this study. The first ANN model consisting of two input neurons (*R(t)* and *Q(t-1)*) while the second ANN model consisted of three input neurons (*R(t,)* *R(t-1)* and *Q(t-1)*). Thus the two ANN investigated were *2-N1-1* and *3-N2-1*. The data need to be encoded and normalized before being applied to ANN. In this study, the data were normalized between 0 and 1. The values of number of hidden neurons (N1 and N2) were determined through training of various architectures and are explained next.

4.3.5.2 Training of ANN Models

The purpose of training of an ANN is to determine the set of connection weights and thresholds that cause the ANN to estimate outputs that are sufficiently close to target values. The data to be employed for training should contain sufficient patterns so that the network can mimic the underlying relationship between input and output variables adequately. In this study, MATLAB neural network toolbox was used to simulate feed-forward back propagation ANN. Following are the MATLAB functions which were used in this study: Network type – Feed-forward back propagation, Input ranges: 0-1, Training

function – TRAINLM, Adaption learning function – LEARNGDM, Performance function – MSE, Transfer function – LOGSIG.

Most of the ANN applications reported so far employ the trial and error method for training the ANN models and determine the optimal architecture for a given data set. However, there are many practical difficulties in the trial and error method as there are no definite guidelines for the same. For example, there are no definite guidelines regarding (a) what should be the acceptable level of global error at the output layer for a particular architecture, (b) when the training should be stopped to prevent under-training and over-training. In the absence of any definite guidelines, the training process adopted may result in (a) an ANN model that is not the best for the given data set, (b) an ANN model that is highly sensitive to the initial solution (initial random weights), and (c) an over-trained or an under-trained ANN model. An over-trained ANN model would tend to perform better during training than in testing, and the trend will be reverse for an under-trained network. There are two approaches that are normally used to train the ANN models. In the first approach, the total data set is first divided into two parts, training set and testing set. The ANN model is trained on the training set and validated on the testing data set. However, it is not clear when to stop the training in this approach. Normally, if the global error becomes less than or equal to a pre-decided acceptable level of global error, then the training is stopped. Another stopping criteria used is the maximum number of iterations up to which the program is allowed to train the ANN. In another approach, the total data set is divided into three sets, a training set, a validation set, and a testing set. The training and validation sets are used to train the ANN model. If we consider the global error at the output layer (normally, MSE) as a function of the training iterations, it is observed to be a continuously decreasing curve during training. However, this curve can start increasing after certain number of iterations for the testing and/or validation data set. Therefore, the training is stopped at the number of iterations at which the global error starts increasing during the validation set. Although this is expected to ensure that the error statistics during training and validation sets will be compatible, it may not be able to ensure that the error statistics during the testing data set will also be of

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acceptable levels of global error. In this study, all the architectures were trained and tested using levels of acceptable error of varying 10^{-1}, 10^{-2}, 10^{-3}, 10^{-6}, 10^{-8}, and 10^{-10}. In addition, four standard statistical parameters: coefficient of correlation R, Nash-Sutcliffe efficiency E, average absolute relative error (AARE), and root mean square error (RMSE) (explained in the next chapter), were computed during both training and testing data sets for different levels of acceptable global error. Then the difference between the training and testing error statistics (ΔR, ΔE, ΔAARE, and ΔRMSE) were plotted against the acceptable levels of global error for each of the architecture investigated. The level of acceptable global error corresponding to minimum differences between training and testing errors was selected as the best model for a particular architecture. For example, the plots of global error v/s differences in various error statistics from 2-5-1 ANN architecture are shown in Figure 4.23 and 4.24. It is clear from these figures that for the 2-5-1 ANN architecture for the rainfall-runoff problem under consideration, an acceptable error level of 10^{-6} gives the least difference between training and testing statistics. Thus, this level of acceptable global error at the output layer of a 2-5-1 ANN model for the data set given would result in the best performance that would avoid any under-training or over-training of the network. It is to be noted that one needs to look at the actual error levels also (and not just the Δerror) to select the best acceptable level of global error to be employed during training. For example, it is clear from these graphs that for an acceptable error level of 10^{-1} also, the Δerror for most of the error statistics are minimum but the actual levels of errors (R, E, AARE, and RMSE) were quite high.

Further, the sensitivity of the initial solution on the final solution for each of the architectures was tested by developing fifteen different models for each of the architectures having different initial solutions. The differences in training and testing error statistics from fifteen different ANN models was computed for each of the architectures. The ANN architecture with a starting solution resulting in the least difference in training and testing error statistics (and actual levels of errors) was then selected as the best ANN model for a particular architecture. For example, for the 2-5-1 ANN architecture, the difference in training and testing error statistics for fifteen different ANN models having different initial solutions are shown in Figures 4.25

through 4.26. The 8th network was selected as the best 2-5-1 ANN model for the data set considered. Similarly, for each architecture, the best network was chosen and that network was trained at optimum level of acceptable error for that particular architecture. The results in terms of various standard statistical performance evaluation criteria from various architectures are presented in the Appendix-A and those from the best architecture are presented and discussed in the next chapter.

The above procedure was adopted for computing the statistical results during training and testing for various architectures with number of hidden neurons ranging from 2 to 11 for both the ANN models. The architecture with the certain number of hidden neurons performing the best in terms of both training and testing results was then selected as the best.

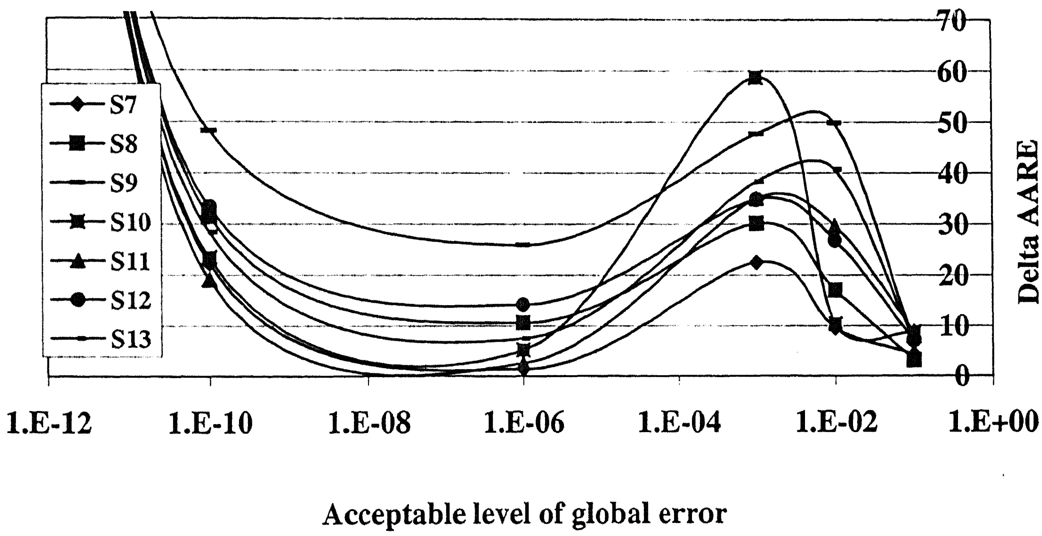


Figure 4.23: Plot of Acceptable level of global error and Difference Between Training and Testing AARE (training S6) from ANN 2-5-1 Model

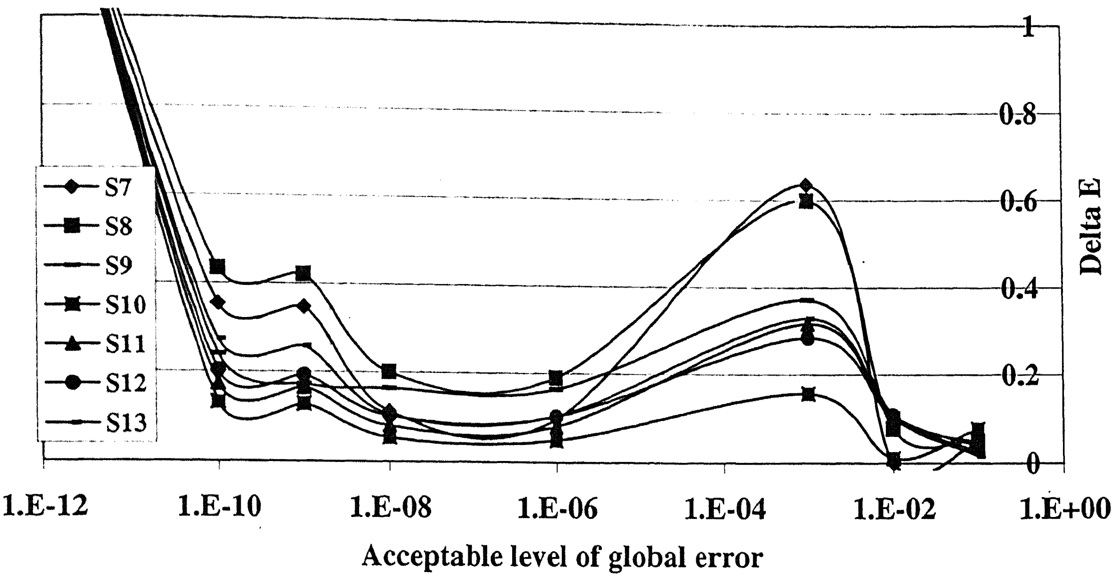


Figure 4.24: Plot of Acceptable level of global error and Difference Between Training and Testing E (training S6) from ANN 2-5-1 Model

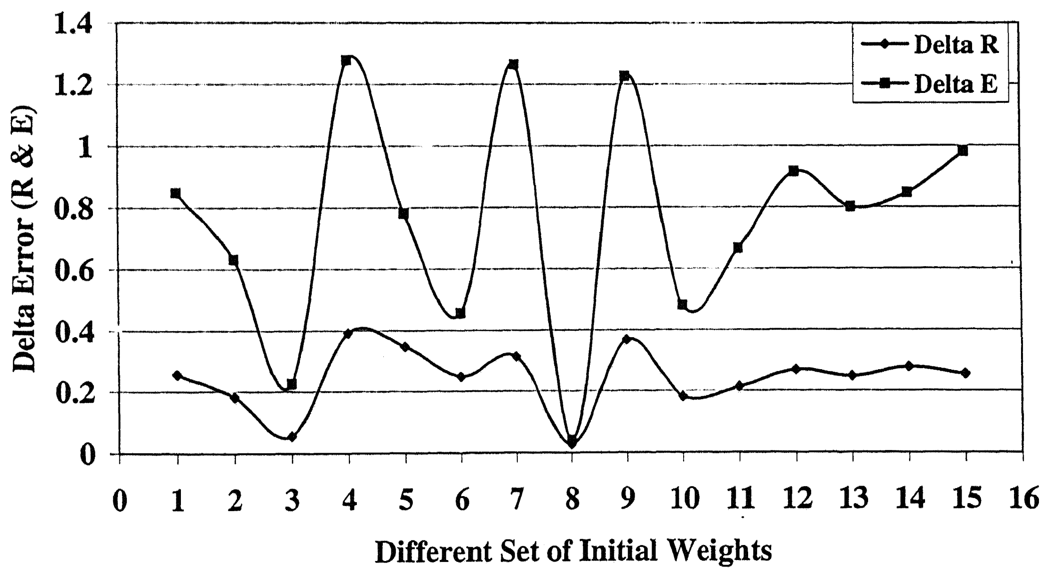


Figure 4.25: Difference In Performance During Training And Testing For ANN 2-5-1 Model For Different Initial Set Of Weights

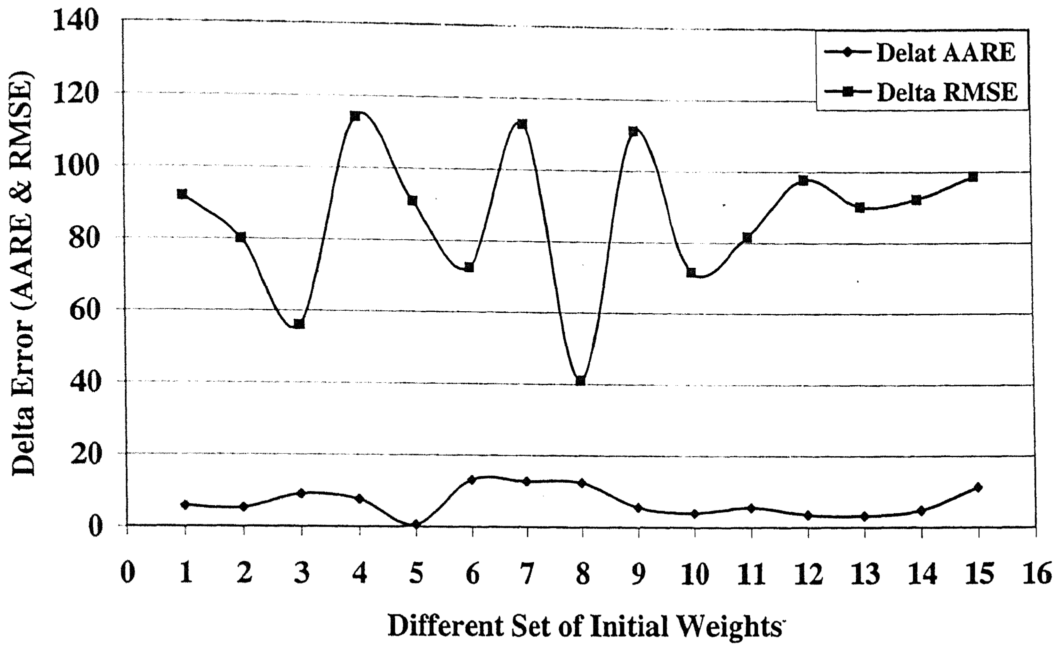


Figure 4.26: Difference in Performance during Training and Testing for ANN 2-5-1 Model For Different Initial Set Of Weights

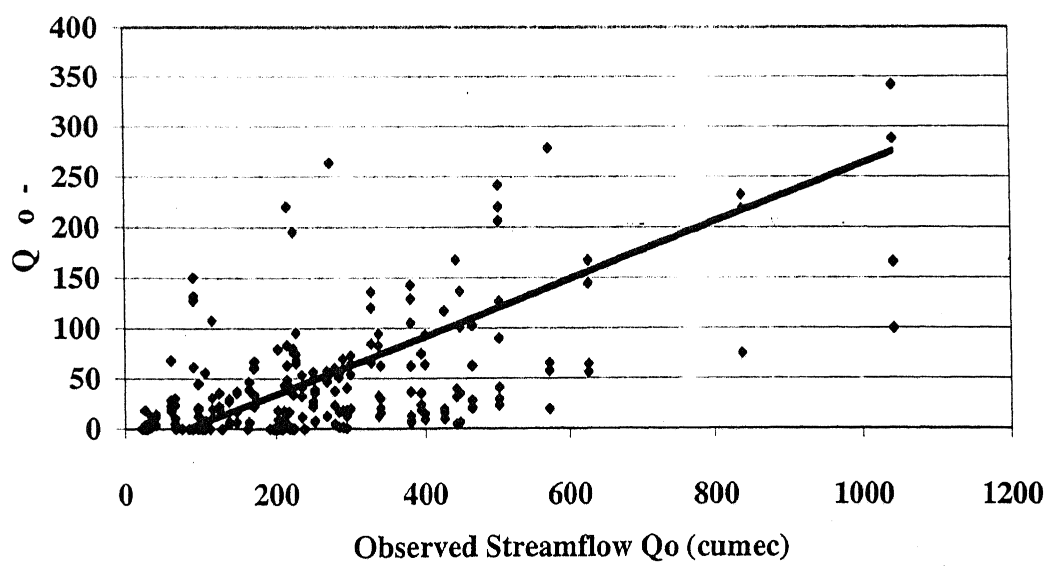


Figure 4.27: Scatter Plot of Observed and Difference Between Observed and Predicted Streamflow from UH Model During Validation

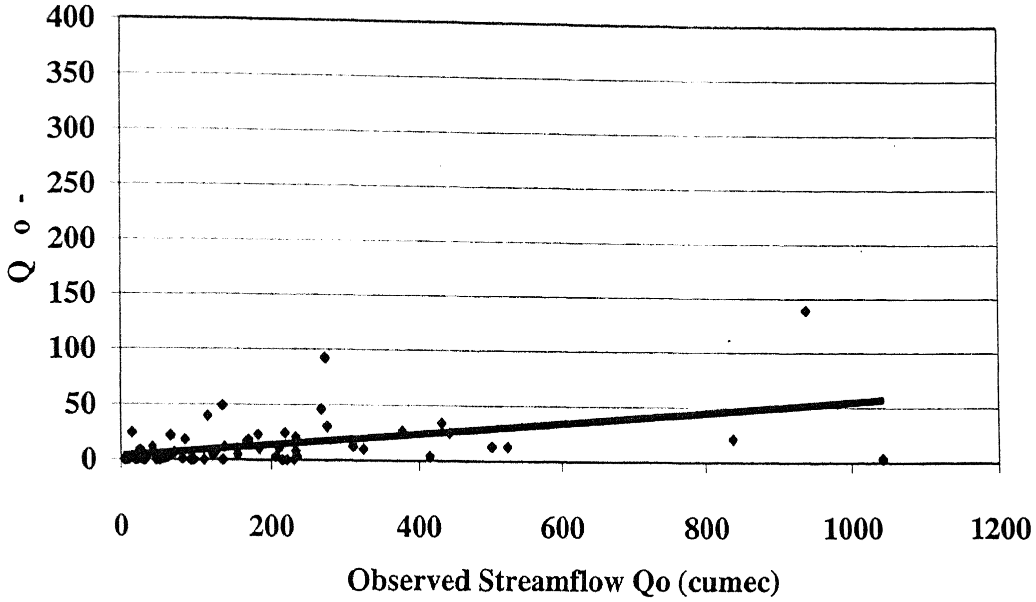


Figure 4.28: Scatter Plot of Observed and Difference Between Observed and Predicted Streamflow from NASH Model During Calibration

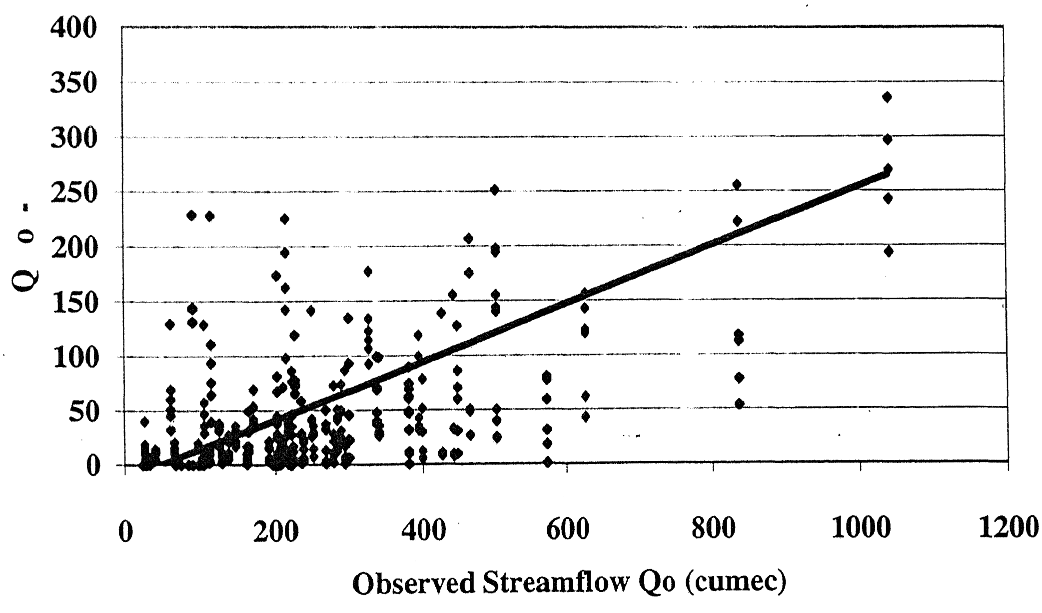


Figure 4.29: Scatter Plot of Observed and Difference Between Observed and Predicted Streamflow from NASH Model During Validation

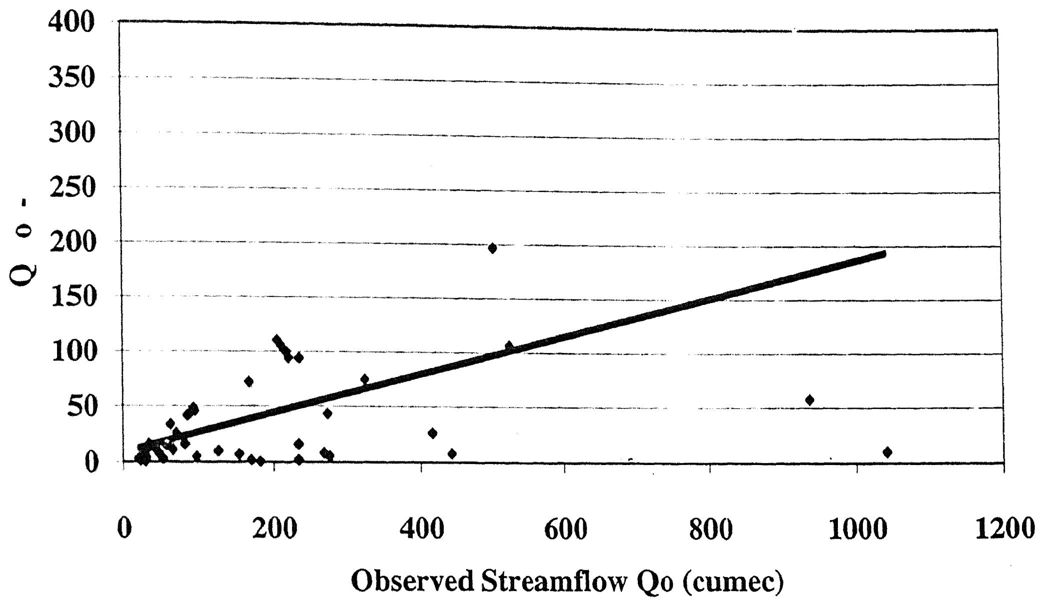


Figure 4.30: Scatter Plot of Observed and Difference Between Observed and Predicted Streamflow from ANN 3-10-1 Model During Training

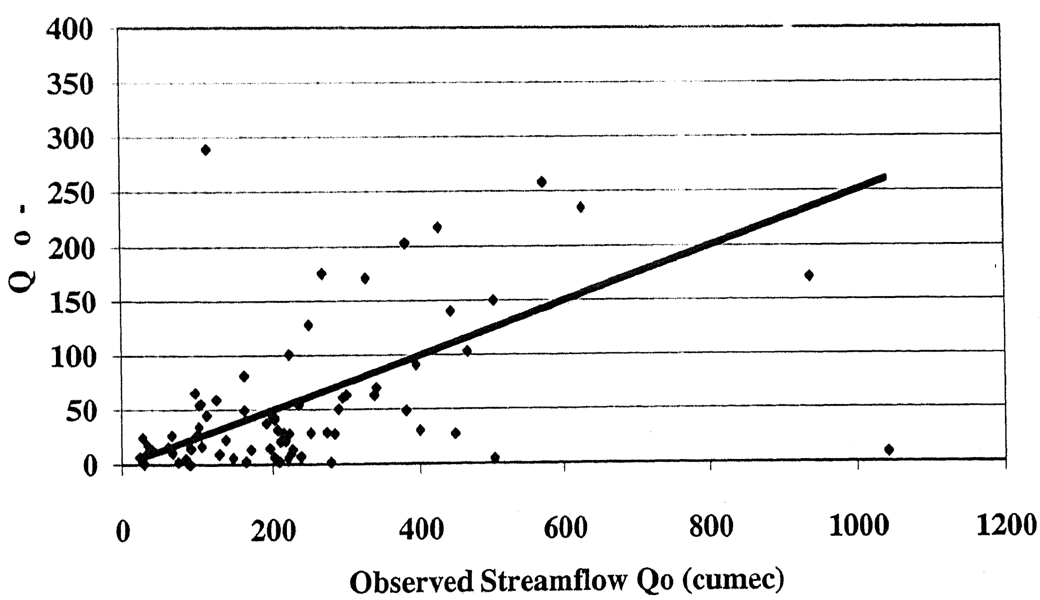


Figure 4.31: Scatter Plot of Observed and Difference Between Observed and Predicted Streamflow from ANN 3-10-1 Model During Testing

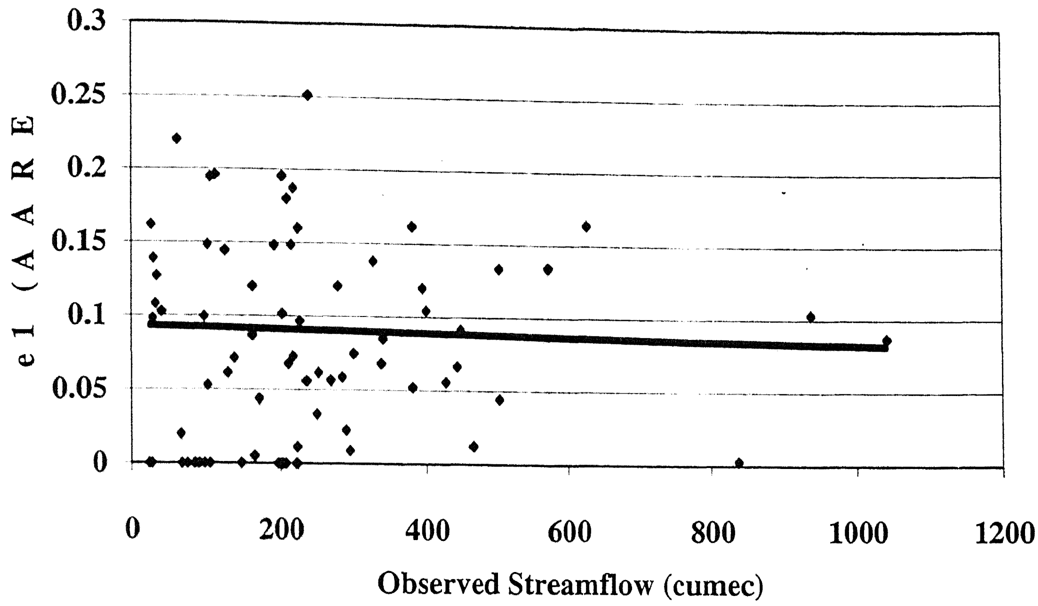


Figure 4.32: Behaviour of e1 With Flow Magnitude from UH Model

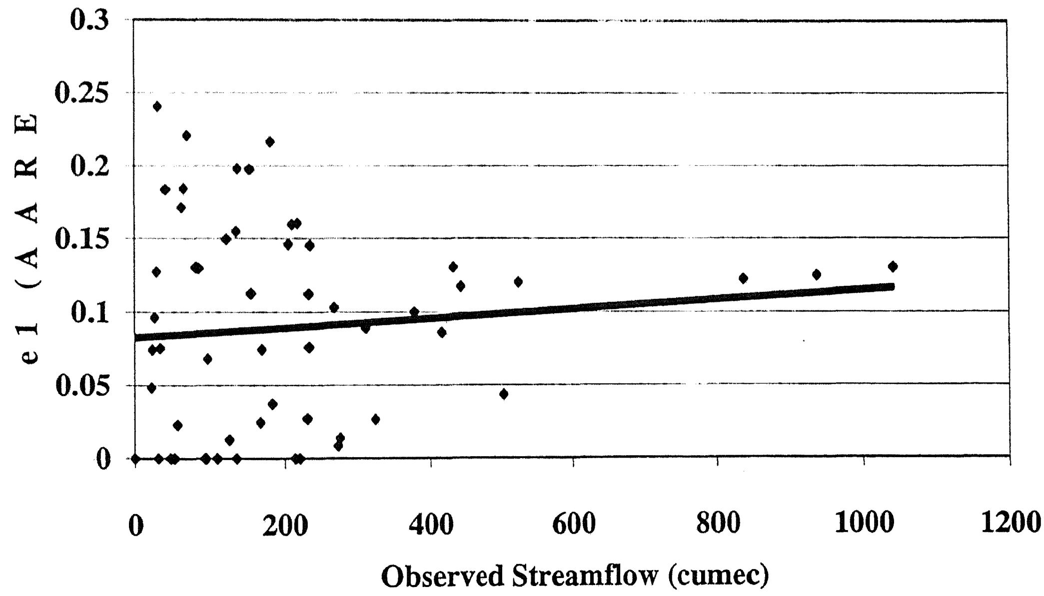


Figure 4.33: Behaviour of e1 With Flow Magnitude from ANN 2-5-1 Model

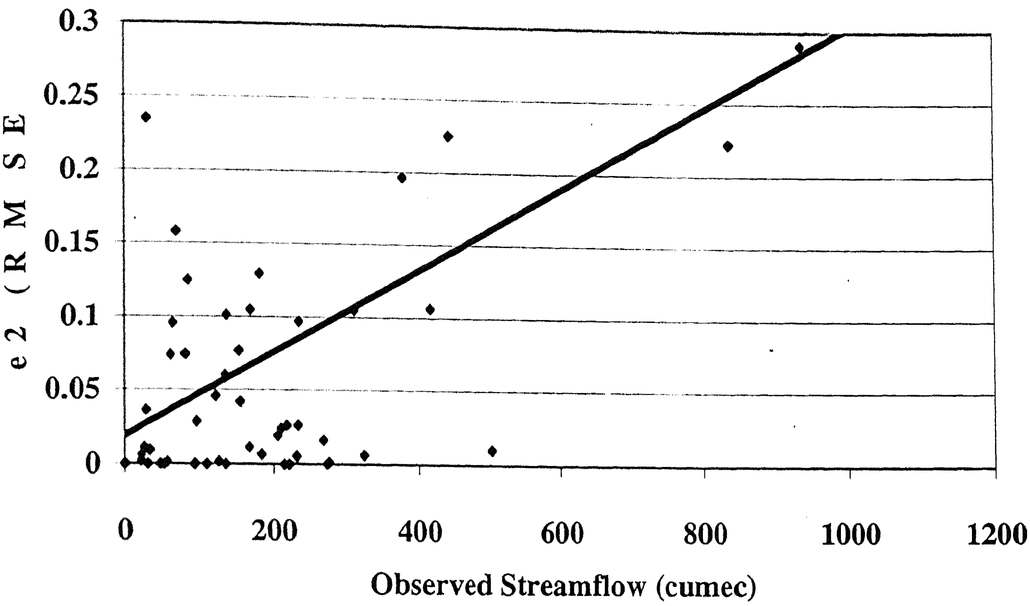


Figure 4.34: Behaviour of e2 With Flow Magnitude from UH Model

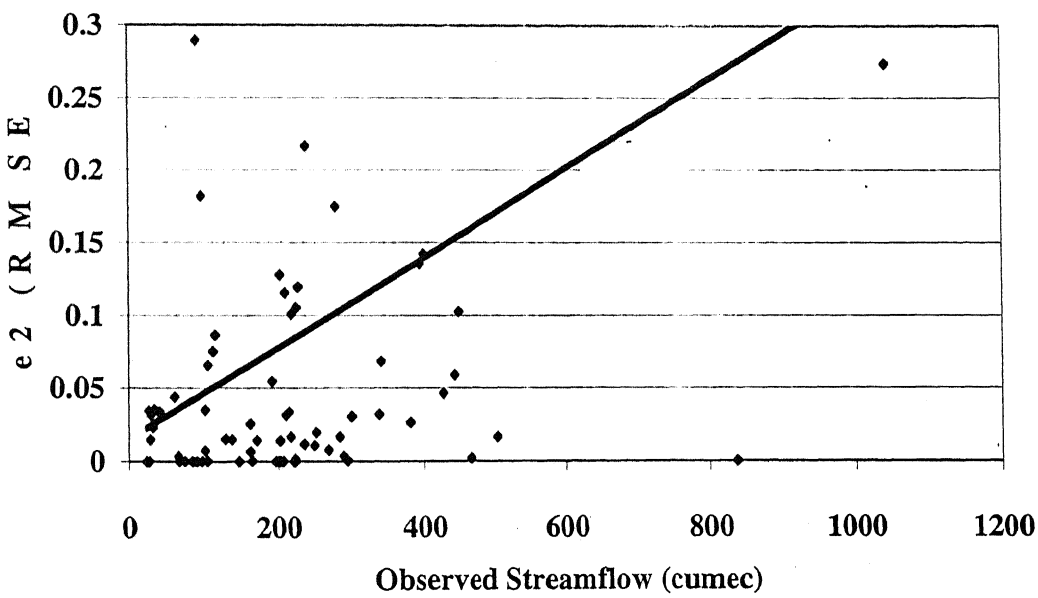


Figure 4.35: Behaviour of e2 With Flow Magnitude from ANN 2-5-1 Model

Mathematically it can be expressed as:

$$r = \frac{S_{o,c}}{S_o S_c} \tag{5.1}$$

$$S_{o,c} = \frac{1}{N-1}\sum_{i=1}^{N}\left(Q_{o,i} - Q_{o,mean}\right)\left(Q_{c,i} - Q_{c,mean}\right) \tag{5.2}$$

$$S_o = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(Q_{o,i} - Q_{o,mean}\right)^2} \tag{5.3}$$

$$S_c = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(Q_{c,i} - Q_{c,mean}\right)^2} \tag{5.4}$$

Where $S_{o,c}$ is correlation between observed and computed, S_o is standard deviation of observed, S_c is standard deviation of computed, $Q_{o,i}$ is observed streamflow, $Q_{c,i}$ is computed streamflow, N is total number of data, $Q_{o,mean}$ is the mean of the observed streamflow and $Q_{c,mean}$ is the mean of the computed streamflow.

(ii) Nash-Sutcliffe Efficiency (E):

Some time coefficient of correlation may not be enough to quantify the strength of relationship. Nash-Sutcliffe efficiency is another statistical parameter normally employed. Mathematically it can be represented by the following equation:

$$E = \frac{E_1 - E_2}{E_1} \tag{5.5}$$

Where

$E_1 = \sum (Q_{o,i} - Q_{o,mean})^2$ Initial variance

$E_2 = \sum (Q_{c,i} - Q_{o,i})^2$ Residual variance

The evaluation scheme for the Nash/ Sutcliffe efficiency is normally taken as follows:

Efficiency E	goodness of fit
< 0.2	Insufficient
0.2 – 0.4	Satisfactory
0.4 – 0.6	Good
0.6 – 0.8	Very good
>0.8	Excellent

(iii) Average Absolute Relative Error (AARE)

AARE is the average of the absolute values of the relative errors in forecasting a certain number of DRH ordinates. To find AARE, we need to first find the relative error (RE) in forecasting a data point. RE is a measure of the error in forecasting a particular variable relative to its exact value. Mathematically, following equation can represent it:

$$RE(i) = \frac{Q_{o,i} - Q_{c,i}}{Q_{o,i}} \times 100\% \tag{5.6}$$

Where, RE(i) is the relative error in forecasting, $Q_{o,i}$ is the observed streamflow and $Q_{c,i}$ is the computed streamflow. The relative error RE(i) can be either positive or negative. Using absolute relative error, AARE can be evaluated as follows:

$$AARE = \frac{1}{N}\sum_{i=1}^{N}|RE(i)| \tag{5.7}$$

Where, N is the total number of data point computed. It is obvious, lower AARE value represents good model performance, and vice versa.

(iv) Threshold Statistics (TS)

It is another important parameter to quantify the performance of a model. It measures the model performance at a certain level of absolute relative error (ARE). The threshold statistics can be defined as the percentage of data points predicted for which the ARE is less than a certain level of relative error (say p%). Mathematically, TSp can be represented by,

$$TS_p = \frac{n_p}{N} \times 100\% \tag{5.8}$$

Where n_p is the number of data points whose ARE is less than p% and N is the total number of data points. It is obvious that higher the threshold statistics values the better the model performance. In this study, the TS statistics has been calculated at ARE 1%, 5%, 10%, 25%, 50%, and 100%.

(v) Normalized Mean Balance Error (NMBE)

NMBE is the average of measure of under-prediction or over-prediction in estimating the runoff discharge. Mathematically, it can be represented by the following equation:

$$NMBE = \frac{\frac{1}{N}\sum_{i=1}^{N}(Q_{c,i} - Q_{o,i})}{\frac{1}{N}\sum_{i=1}^{N}Q_{o,i}} \times 100\% \tag{5.9}$$

The positive value of NMBE represents over-prediction and vice-versa.

(vi) Root Mean Square Error (RMSE)

The RMSE is another statistical parameter which is employed to measure the residual error from model. Mathematically it is expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_{o,i} - Q_{c,i})^2}{N}} \tag{5.10}$$

5.3 Discussion of Results

The results from different models developed in this study were obtained in two ways. First, in terms of six different standard statistical parameters and second in terms of scattered plot. Results were calculated for both calibration/training data set and validation/testing data set to choose the best model. Few sample results from each type of model are presented in this chapter and remaining results are provided in Appendix. The results in terms of the various performance evaluation criteria from all the models structures are presented in Appendix-A and those from the best models are presented in this chapter. The results in terms of statistical parameters from combined or averaged approach are presented in Table 5.1 and those from the four categories are presented in Table 5.2 through 5.5, respectively. The discussion of the results has been divided into two parts: results for combined input and the results for category-wise input.

5.3.1 Results for Combined Input

The results in terms of R, E, AARE, TS, NMBE, and RMSE from various models for combined input during both calibration and validation are presented in Table 5.1. It can be observed from Table 5.1 that during calibration/training among the CRR models, the UH model performed the best and among the ANN models the 3-10-1 ANN model performed the best. The UH model obtained the best values of R, E, AARE, NMBE, and RMSE statistics of 0.9850, 0.9701, 11.56%, 0.02, and 36.28, respectively, and the performance of the UH model was the best in terms of various TS statistics also. The performance of the NASH model was comparable to that of the UH model but the

performances of Clark-1, Clark-2, and the TANK models were only reasonable. Further, the performances of the UH and the 3-10-1 ANN model was comparable in terms of R, E, NMBE and RMSE statistics but UH model performed better than the 3-10-1 ANN model in terms of TS and AARE statistics. Thus, the UH model can be considered to be the best during calibration/training when the rainfall and runoff data combined from all the storms were used as input in developing the various models.

Analyzing the results during validation/testing from Table 5.1, it can be observed that the 3-10-1 ANN model performed the best in terms of R, E, NMBE, and RMSE statistics (0.9610, 0.9233, 0.00, and 55.82, respectively) while the UH model performed the best in terms of most of the TS and AARE (17.66%) statistics. However, it is worth mentioning that all the flow values predicted from the 3-10-1 ANN model had absolute relative error (ARE) of less than 100% (see TS100 in Table 5.1) while no other model was able to achieve this. Also, the 3-10-1 ANN model was completely unbiased towards under-prediction or over-prediction (NMBE = 0.0). Thus, it can be said that even through the UH model performed marginally better than the 3-10-1 ANN model during calibration/training, it was not able to perform better during validation/testing. Considering the fact that the performance of the 3-10-1 ANN model was comparable to the UH model during calibration/training, it can be said that the 3-10-1 ANN model was the best in modeling the event-based rainfall-runoff process in the Kentucky River basin when data from many storms varying in peak magnitudes are combined while developing the models. This demonstrates the robustness of the ANN technique in developing the complex, dynamic, and highly non-linear rainfall-runoff relationships when presented with data of varying magnitudes and nature.

5.3.2 Results for Category-wise Input

The rainfall and runoff data from all the available storms were divided into four categories depending upon the peak magnitude of the flow values as discussed earlier. All the model structures were investigated using the category-wise data in order to test their suitability of various models in modeling the complex rainfall-runoff process of

varying degree and complexity depending upon the peak magnitude. The data from all the storms were divided into four categories. The results from the four categories are presented in Table 5.2 through Table 5.5, respectively. The discussion of results for each category is discussed next. Please note that the calibration results from the UH model are not included in these tables as when a UH is applied to the calibration storm it would produce the same storm giving the perfect error statistics.

Results for Category-I

The results in terms of various performance evaluation criteria from various models developed using the data in Category-I are presented in Table 5.2. It is clear from Table 5.2 that the NASH model performed the best during calibration in terms of all statistical parameters (apart from the UH model) except for NMBE, for which the 2-5-1 ANN model performed the best. The NASH model obtained the best values of R, E, AARE, and RMSE statistics of 0.8779, 0.8707, 7.03%, and 6.62, respectively, during calibration. Analyzing the results during validation from Table 5.2, it can be observed that the UH model performed the best during validation in terms of most of the performance statistics barring a few exceptions. For example, the UH model obtained the best R, AARE, NMBE, and RMSE statistics of 0.8871, 12.12%, 0.06, and 16.75, respectively; and the NASH model obtained the best E statistic of 0.8451. Although the performances of both the ANN models were reasonable, they were not better than the CRR models for category-I. Thus, it can be concluded that the performances of the conceptual models was better than the ANN models and the UH model can be used to model the event-based rainfall-runoff process for Category-I for the data under consideration.

Results for Category-II

The results in terms of various performance evaluation criteria from various models developed using the data in Category-II are presented in Table 5.3. It can be observed from Table 5.3 that during calibration/training, the NASH model performed the best in terms of E, AARE, and RMSE statistics (values 0.9650, 7.20%, 10.75, respectively), and

most of the TS statistics (apart from the UH model); Clarke-2 model performed the best in terms of R (0.9740), and the 2-6-1 ANN model performed the best in terms of NMBE statistic (0.87). Thus, there was no clear cut winner among all the models developed for Category-II during calibration although UH and NASH models may be preferred over the other models. Analyzing the results during validation/testing for Category-II from Table 5.3, it can be observed that the NASH model performed the best in terms of R, E, and AARE statistics (values 0.9770, 0.9425, and 8.18%, respectively) and some TS statistics; the UH model performed the best in terms of NMBE and RMSE statistics (values -0.11 and 10.49, respectively), and some of the TS statistics. Again the performance of both the ANN models was found to be only moderate in comparison to the CRR models during validation also. In summary, it can be said that the conceptual models performed better than the ANN models and either UH or NASH model can be used to model the event-based rainfall-runoff process for Category-II.

Results for Category-III

The results in terms of various performance evaluation criteria from various models developed using the data in Category-III are presented in Table 5.4. It can be observed from Table 5.4 that during calibration/training, the NASH model performed the best in terms of R, E, AARE, NMBE, and RMSE statistics (values 0.9891, 0.9739, 5.89%, -0.12, and 18.59, respectively), and all of the TS statistics. Further, the 2-10-1 ANN model was the joint best in terms of TS1 and TS5 statistics. Clearly, the performance of the NASH model was excellent and was the best model during calibration for Category-III (apart from UH). Analyzing the results during validation/testing for Category-III from Table 5.4, it can be observed that the UH model consistently outperformed the rest of models in terms of all the statistical parameters. It obtained the best values of R, E, AARE, NMBE, and RMSE statistics of 0.9902, 0.9790, 3.08%, 0.01, and 15.40, respectively. The next best model was 3-3-1 ANN model in terms of AARE and NMBE statistics; and the NASH model in terms of R, E, and RMSE statistics. The performance of the ANN models was found to be comparable to the other CRR models during both calibration and validation for Category-III. In summary, it can be said that the UH model is the most

suitable model for modeling the event-based rainfall-runoff process for Category-III; the performance of the NASH and 3-3-1 ANN model was the next best; and the performance of the other CRR and ANN models was moderate and comparable to each other.

Results for Category-IV

The results in terms of various performance evaluation criteria from various models developed using the data in Category-IV are presented in Table 5.5. It can be observed from Table 5.5 that during calibration/training, the NASH model performed the best in terms of R, E, AARE, and NMBE statistics (values 0.9793, 0.9709, 8.09%, and -0.11, respectively), and all of the TS statistics; and the 2-3-1 ANN model performed the best in terms of the RMSE statistics. Further, the 3-3-1 ANN model was the next best model in terms of most of the performance statistics. Clearly, the performance of the UH model was excellent and it was the best model during calibration for Category-III; NASH model was the next best; and the 3-3-1 ANN model was the next best model after UH and NASH models. Analyzing the results during validation/testing for Category-III from Table 5.5, it can be observed that the UH model consistently outperformed the rest of models in terms of all the statistical parameters. It obtained the best values of E, AARE, NMBE, and RMSE statistics of 0.8926, 9.17%, 0.00, and 51.52, respectively); and the NASH model obtained the best R value of 0.9716. The performance of the ANN models was not found to be very good. In summary, it can be said that the UH model is the most suitable model for modeling the event-based rainfall-runoff process for Category-IV; and the performance of the NASH model was the next best.

5.3.3 Analysis of Various Performance Statistics

In most of the CRR and ANN applications, the performance of the models is normally evaluated using a few error statistics such as R, MSE, and RMSE, etc. The performance of various models developed was analyzed using a wide variety of standard performance statistics in this study. The error statistics normally employed, such as R, MSE, and RMSE, involve the square of the deviations between predicted and observed values of the

variable being modeled. Therefore, such statistics tend to be biased towards the high magnitudes of the variable being modeled. As such, these statistics tend to be dominated by the high magnitude flows and the low magnitude flows are not properly represented in them. The error statistics that are not biased towards either high magnitude or low magnitude would be more desirable. The average absolute relative error (AARE) is one such statistic that is relative to the observed values and is not biased towards any magnitude flow. In order to verify this claim, an analysis of these error statistics is needed. Such an analysis was carried out in this study and the findings are reported here.

It is expected that as the magnitude of flow (Q_O) increases, the difference between the observed flow and predicted flow $(\Delta\{Q_O-Q_P\})$ would also increase. This can be easily verified by plotting the observed flow against the corresponding difference in the observed and predicted flow. The QO versus $\Delta\{Q_O-Q_P\}$ plots from UH, NASH, and ANN models are shown in Figure 4.27 through 4.31, respectively. These figures clearly indicate that as the magnitude of flow increases, the deviation between observed and predicted flow would also increase. This would mean that the error statistics such as MSE and RMSE would be dominated by the high magnitude flows. However, that would not be the case for unbiased statistics such as AARE. In order to verify that the AARE is a better performance statistic than RMSE, a further analysis of the results is needed. Such an analysis should be able to evaluate the impact of the magnitude of the flow value on the error statistic (AARE and RMSE). A performance statistic can be considered a better one if it does not vary with the magnitude of the variable being modeled.

Let us define two additional error statistics e1 and e2. The error statistic e1 is nothing but the ratio of the absolute relative error in predicting a flow value (ARE(i)) to the overall AARE in predicting a total of N flow values. Similarly, the error statistic e2 is defined as the ratio of the contribution of an individual data point to the RMSE (RMSE(i)) to the overall RMSE in estimating a total of N flow values. Figure 4.32 through Figure 4.33 show the e1 versus Q_O plot from UH and ANN models; while the Figures 4.34 through Figure 4.35 show the e2 versus Q_O plots from the UH and ANN models. It can be seen from these plots that as the value of the observed flow increases, the contribution to

RMSE also increases but the contribution to overall AARE from an individual data point remains constant. This clearly suggests that AARE is an unbiased performance statistic that does not depend upon the magnitude of flow and should be preferred over the conventional use of error statistics such as MSE and RMSE etc.

Table 5.1: Performance Evaluation Criteria from Various Models (Combined Input)

STORM	MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training												
	UH	0.9850	0.9701	11.56	37.9	45.5	65.2	89.4	97.0	100.0	0.02	36.28
	NASH	0.9814	0.9617	15.82	19.7	37.9	60.6	81.8	92.4	100.0	2.03	41.07
	CLARK-1	0.9227	0.8305	29.82	18.2	24.2	30.3	54.6	84.9	95.5	-3.75	86.42
	CLARK-2	0.9585	0.8940	22.73	19.7	28.8	28.8	65.2	89.4	100.0	-3.99	68.33
	TANK	0.8807	0.6496	178.23	1.5	3.0	10.6	28.8	53.0	69.7	-4.97	124.26
	ANN 2-8-1	0.9438	0.8906	55.09	1.5	15.2	24.2	53.0	77.3	87.9	0.91	69.41
	ANN 3-10-1	0.9837	0.9676	50.39	6.1	16.7	34.9	59.1	78.8	87.9	-0.09	37.80
During Validation/Testing												
	UH	0.8315	0.6700	17.66	37.9	42.4	59.1	78.8	93.9	97.0	0.02	116.25
	NASH	0.8124	0.4530	34.60	21.2	33.3	54.6	71.2	83.3	89.4	19.25	149.66
	CLARK-1	0.7990	0.6012	42.19	18.2	22.7	30.3	59.1	78.8	90.9	12.09	127.79
	CLARK-2	0.7992	0.5886	34.54	19.7	27.3	34.9	57.6	81.8	93.9	11.80	129.79
	TANK	0.8920	0.5621	84.25	1.5	7.6	12.1	43.9	62.1	69.7	29.04	133.91
	ANN 2-8-1	0.9099	0.8263	26.91	4.6	12.1	34.9	59.1	84.9	95.5	0.81	83.99
	ANN 3-10-1	0.9610	0.9233	21.00	7.6	25.8	40.9	69.7	90.9	100.0	0.00	55.82

Table 2: Performance Evaluation Criteria from Various Models: Category I

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.8779	0.8707	7.03	27.3	63.6	72.7	90.9	100.0	100.0	-0.08	6.62
CLARK-1	0.8160	0.6395	16.19	18.2	18.2	45.5	81.8	90.9	100.0	-0.50	11.27
CLARK-2	0.8530	0.7028	14.95	18.2	27.3	36.4	81.8	100.0	100.0	-0.73	10.24
TANK	0.8461	0.5884	24.69	0.0	0.0	27.3	54.6	90.9	100.0	-30.92	17.58
ANN 2-5-1	0.7988	0.7709	23.02	9.1	18.2	36.4	54.6	90.9	100.0	-0.01	14.01
ANN 3-4-1	0.8276	0.6175	28.77	0.0	9.1	9.1	54.6	90.9	100.0	7.06	16.80
During Validation/Testing											
UH	0.8871	0.7302	12.12	36.4	36.4	63.6	81.8	100.0	100.0	0.06	16.75
NASH	0.8461	0.8451	21.08	18.2	36.4	45.5	54.6	72.7	90.9	38.36	29.12
CLARK-1	0.7860	0.5800	30.27	18.2	27.3	36.4	45.5	72.7	90.9	37.32	29.20
CLARK-2	0.8660	0.6399	38.78	18.2	18.2	18.2	36.4	72.7	90.9	36.76	21.87
TANK	0.8389	0.5177	65.41	0.0	9.1	9.1	27.3	45.5	72.7	44.20	30.46
ANN 2-5-1	0.8022	0.7506	26.61	9.1	9.1	36.4	54.6	81.8	100.0	-7.73	24.97
ANN 3-4-1	0.7304	0.5821	31.32	0.0	9.1	18.2	36.4	81.8	100.0	5.88	20.85

Table 3: Performance Evaluation Criteria from Various Models: Category II

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9648	0.9650	7.20	27.3	54.6	81.8	90.9	100.0	100.0	5.53	10.75
CLARK-1	0.8280	0.6268	28.89	18.2	36.4	45.5	54.6	90.9	90.9	18.49	35.13
CLARK-2	0.9740	0.8341	20.96	18.2	27.3	36.4	45.5	100.0	100.0	18.05	23.42
TANK	0.8849	0.7049	19.18	0.0	27.3	45.5	63.6	100.0	100.0	-3.21	31.24
ANN 2-6-1	0.8722	0.7426	20.90	18.2	36.4	45.5	63.6	81.8	100.0	0.87	30.10
ANN 3-7-1	0.8898	0.7146	16.46	27.3	45.5	63.6	72.7	90.9	100.0	1.15	22.67
During Validation/Testing											
UH	0.9585	0.8942	12.29	36.4	36.4	45.5	90.9	100.0	100.0	-0.11	10.49
NASH	0.9770	0.9425	8.18	18.2	36.4	81.8	90.9	100.0	100.0	-1.53	21.80
CLARK-1	0.8400	0.6666	21.24	18.2	18.2	45.5	72.7	90.9	100.0	-3.75	52.48
CLARK-2	0.9540	0.8254	13.35	27.3	36.4	45.5	72.7	100.0	100.0	-4.03	37.98
TANK	0.8765	0.6499	22.50	9.1	27.3	36.4	54.6	100.0	100.0	-22.87	60.99
ANN 2-6-1	0.8517	0.7225	19.90	27.3	36.4	36.4	63.6	90.9	100.0	-0.74	62.61
ANN 3-7-1	0.8312	0.7047	23.25	9.1	27.3	45.5	63.6	90.9	100.0	-1.21	73.02

Table 4: Performance Evaluation Criteria from Various Models: Category III

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9891	0.9739	5.89	27.3	54.6	86.4	95.5	100.0	100.0	-0.12	18.59
CLARK-1	0.8230	0.6282	20.86	22.8	22.8	27.3	63.6	95.5	100.0	-4.54	74.19
CLARK-2	0.9390	0.8098	16.19	18.2	27.3	36.4	77.3	100.0	100.0	-4.84	53.47
TANK	0.8974	0.6895	21.52	4.6	27.3	45.5	68.2	90.9	100.0	-8.88	66.81
ANN 2-10-1	0.9333	0.8699	16.54	27.3	54.6	54.6	72.7	90.9	100.0	-0.63	49.18
ANN 3-3-1	0.8634	0.7368	20.25	13.7	31.9	45.5	68.2	86.4	100.0	-0.73	60.73
ANN 3-7-1	0.8806	0.7637	20.40	13.7	41.0	59.1	68.2	86.4	100.0	0.38	58.23
During Validation/Testing											
UH	0.9902	0.9790	3.08	41.0	68.2	100.0	100.0	100.0	100.0	0.01	15.40
NASH	0.9698	0.9420	14.58	18.2	36.4	50.1	77.3	100.0	100.0	16.71	40.22
CLARK-1	0.7790	0.5718	19.01	22.8	27.3	41.0	72.8	95.5	100.0	12.12	70.09
CLARK-2	0.9565	0.7925	13.81	22.8	31.9	50.1	81.8	100.0	100.0	11.82	49.22
TANK	0.8669	0.5962	19.27	0.0	22.8	27.3	68.2	95.5	100.0	-12.93	74.37
ANN 2-10-1	0.8898	0.7774	12.91	0.0	36.4	54.6	90.9	100.0	100.0	-5.37	60.08
ANN 3-3-1	0.8610	0.6681	9.63	0.0	45.5	81.8	90.9	95.5	100.0	-7.00	62.33
ANN 3-7-1	0.8666	0.6549	14.18	4.6	13.7	40.9	90.9	95.5	100.0	-10.84	69.92

Table 5: Performance Evaluation Criteria from Various Models: Category IV

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9793	0.9709	8.09	27.3	63.6	63.6	90.9	100.0	100.0	0.11	53.52
CLARK-1	0.5710	0.1234	42.29	18.2	18.2	18.2	36.4	36.4	100.0	-23.15	194.30
CLARK-2	0.6610	0.1810	39.50	18.2	27.3	27.3	36.4	45.5	100.0	-23.26	184.46
TANK	0.8045	0.4887	39.77	0.0	18.2	27.3	45.5	63.6	100.0	-11.87	124.37
ANN 2-3-1	0.8163	0.5954	27.75	9.1	9.1	27.3	63.6	90.9	90.9	-5.70	48.71
ANN 2-4-1	0.7843	0.4821	32.64	9.1	9.1	9.1	27.3	90.9	100.0	0.90	82.38
ANN 3-3-1	0.7636	0.7677	25.36	18.2	27.3	36.4	63.6	90.9	90.9	0.26	66.13
ANN 3-6-1	0.8572	0.5709	45.08	0.0	9.1	9.1	18.2	45.5	100.0	3.97	123.22
ANN 3-10-1	0.7759	0.3741	17.86	9.1	27.3	45.5	81.8	81.8	100.0	-3.73	122.42
During Validation/Testing											
UH	0.9490	0.8926	9.17	45.5	54.6	63.6	90.9	100.0	100.0	0.00	51.52
NASH	0.9716	0.8922	17.62	18.2	45.5	45.5	81.8	90.9	100.0	16.40	61.67
CLARK-1	0.4710	0.1065	35.34	18.2	18.2	18.2	27.3	63.6	100.0	-12.35	148.62
CLARK-2	0.5930	0.2001	29.71	18.2	18.2	27.3	45.5	72.7	100.0	-12.50	140.63
TANK	0.8913	0.5523	49.36	0.0	0.0	9.1	36.4	54.6	81.8	-19.66	105.20
ANN 2-3-1	0.7281	0.4618	63.33	0.0	0.0	0.0	9.1	54.6	72.7	1.95	99.84
ANN 2-4-1	0.7824	0.6631	35.48	0.0	9.1	18.2	45.5	63.6	100.0	2.43	82.20
ANN 3-3-1	0.7411	0.5041	42.36	0.0	0.0	9.1	27.3	54.6	100.0	-19.05	109.89
ANN 3-6-1	0.6828	0.5059	41.36	9.1	18.2	27.3	45.5	63.6	81.8	7.43	78.13
ANN 3-10-1	0.7312	0.3591	32.65	0.0	0.0	9.1	36.4	81.8	100.0	-8.02	109.49

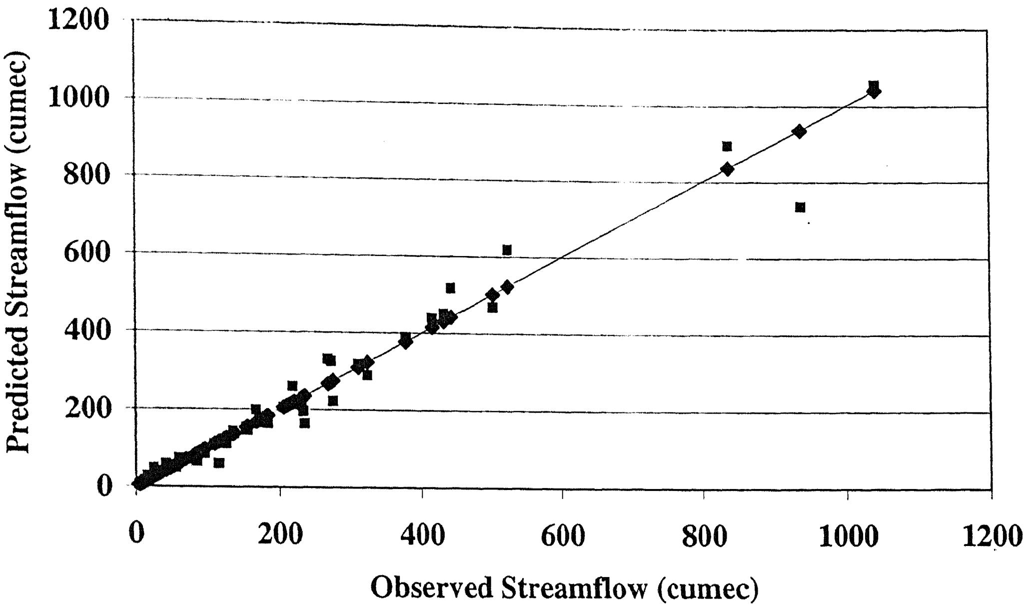


Figure 5.1: Scatter Pot for UH-c Model During Calibration

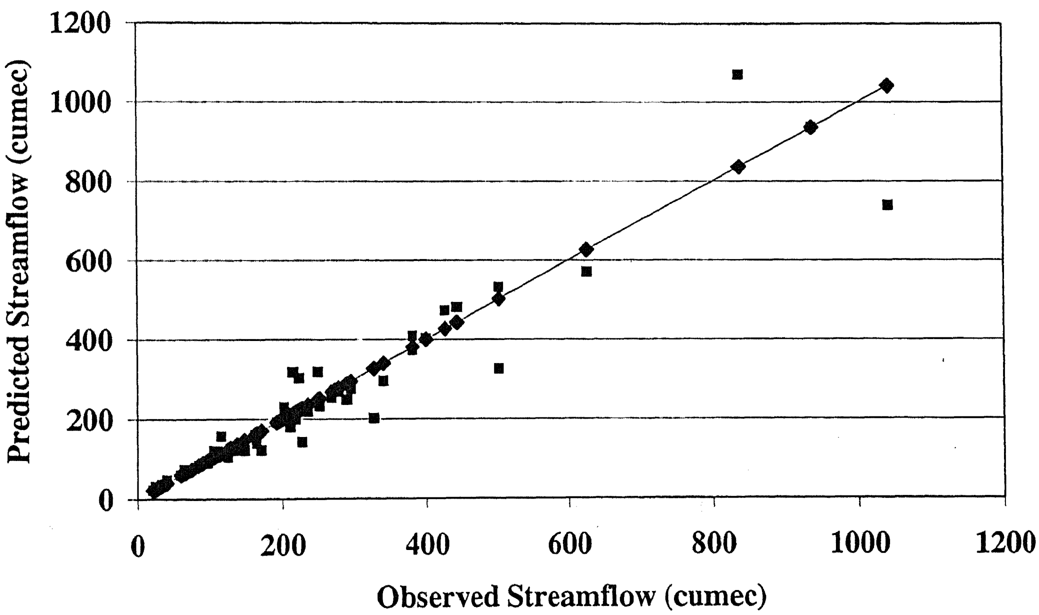


Figure 5.2: Scatter Pot for UH-c Model During Validation

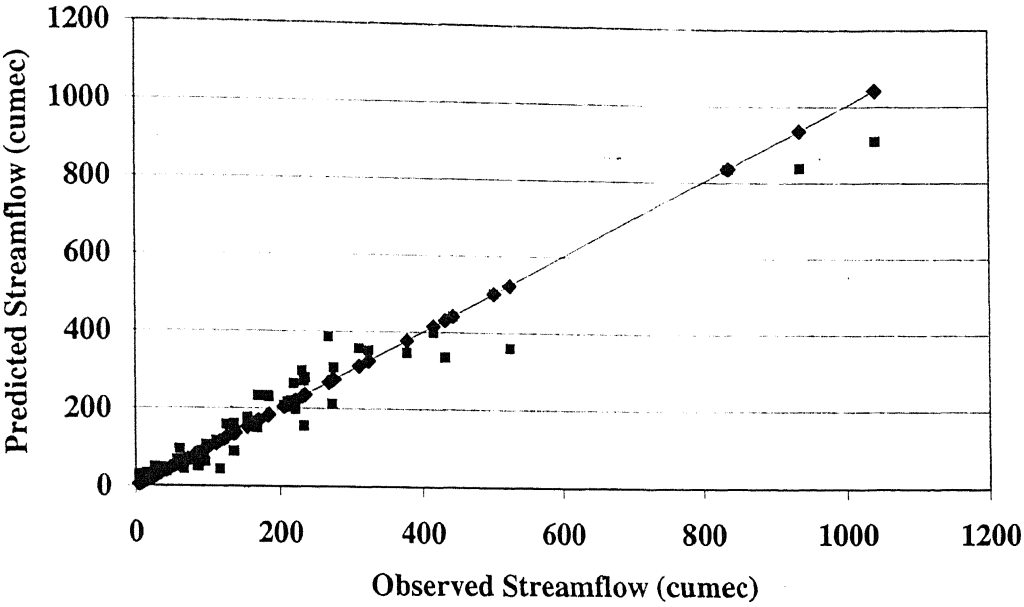


Figure 5.3: Scatter Plot for ANN 2-8-1c During Training

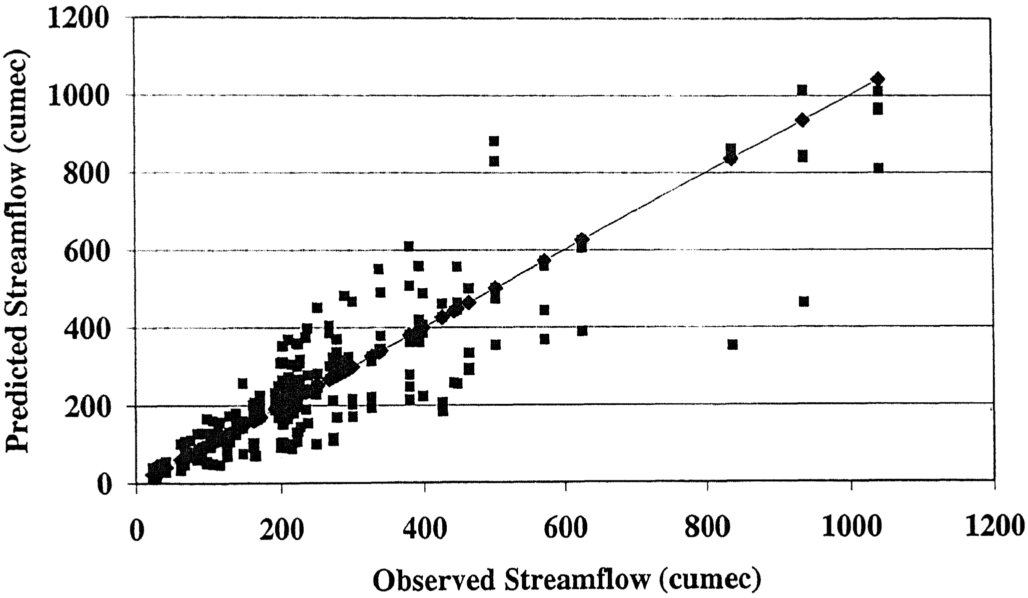


Figure 5.4: Scatter Plot for ANN 2-8-1c During Testing

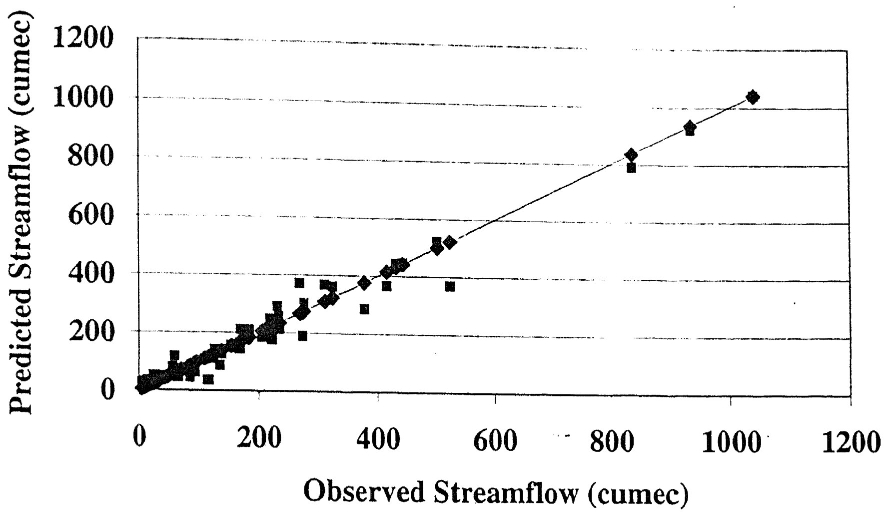


Figure 5.5: Scatter Plot for ANN 3-10-1c During Training

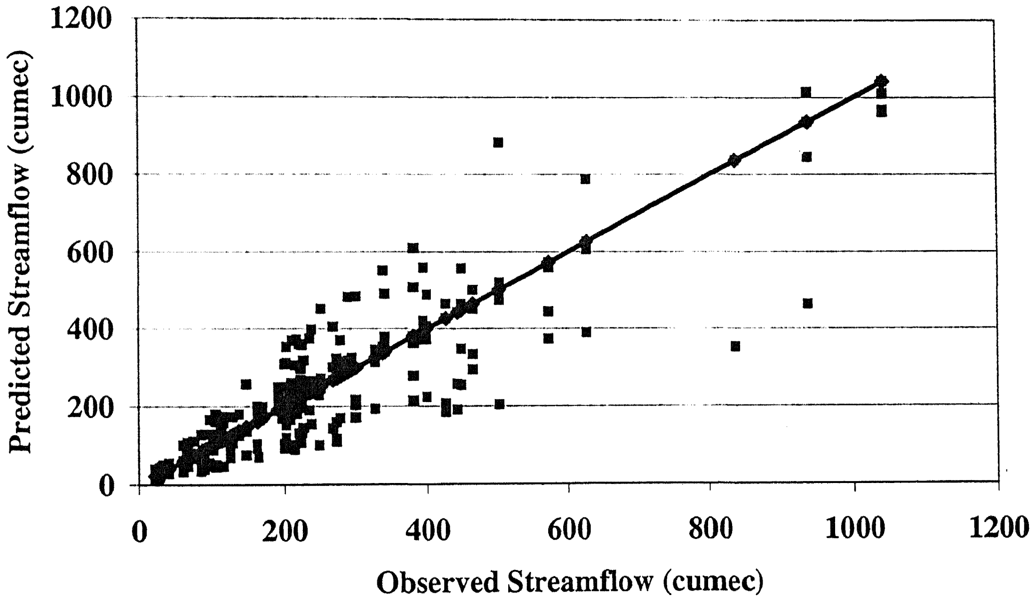


Figure 5.6: Scatter Plot for ANN 3-10-1c During Testing

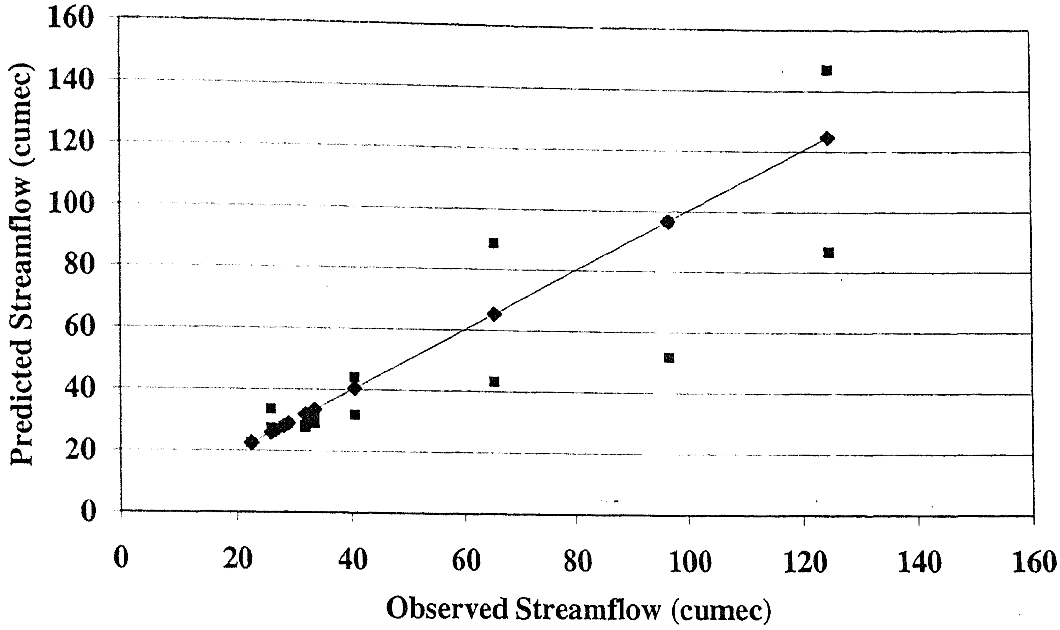


Figure 5.7: UH Model Validation from Category-I Storms

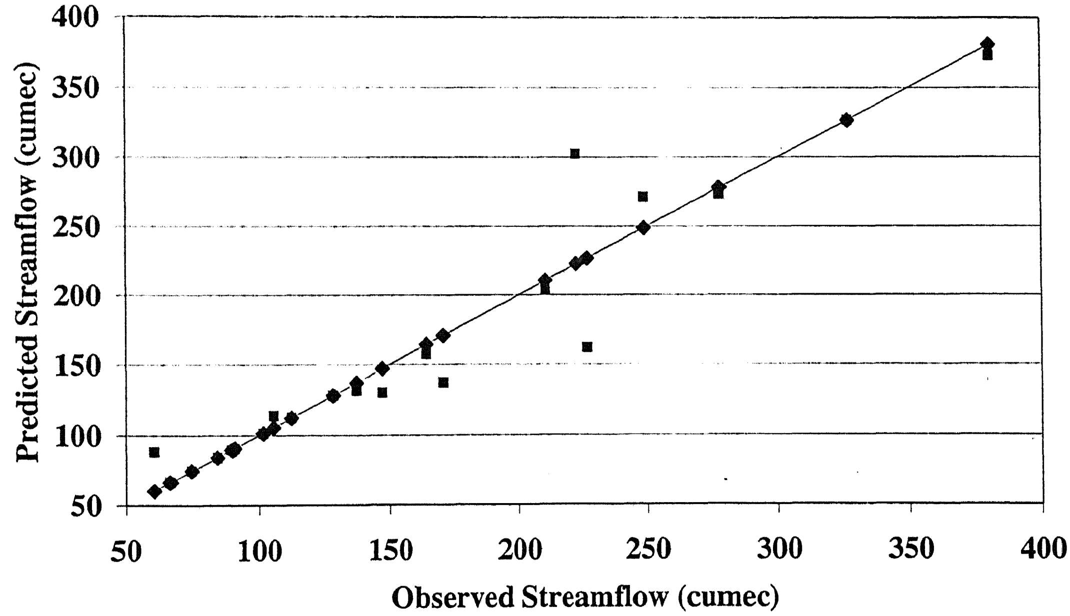


Figure 5.8: UH Model Validation from Category-II Storms

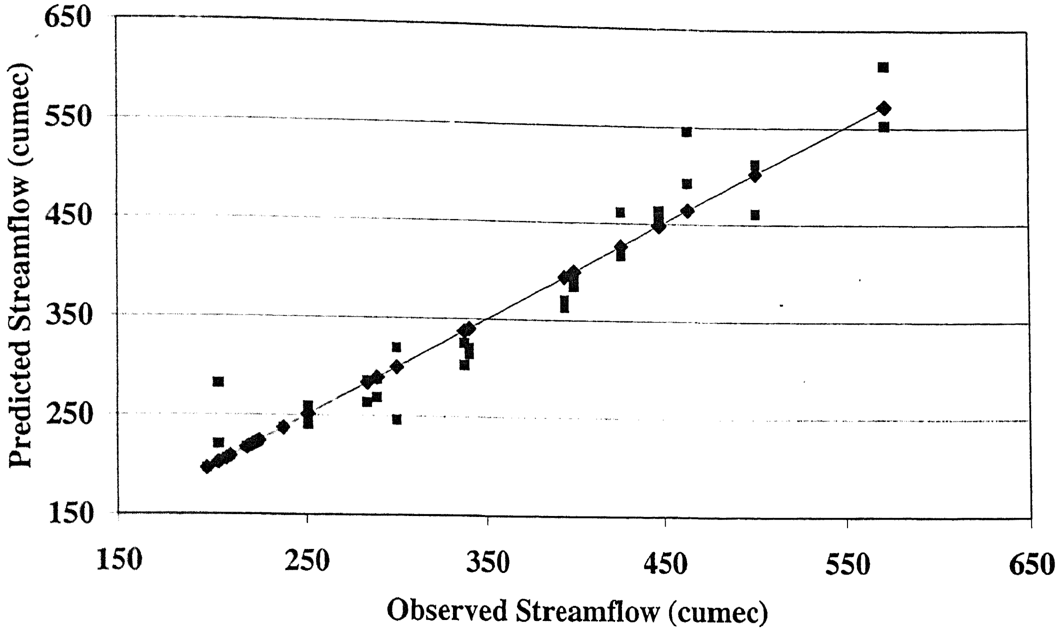


Figure 5.9: UH Model Validation from Category-III Storms

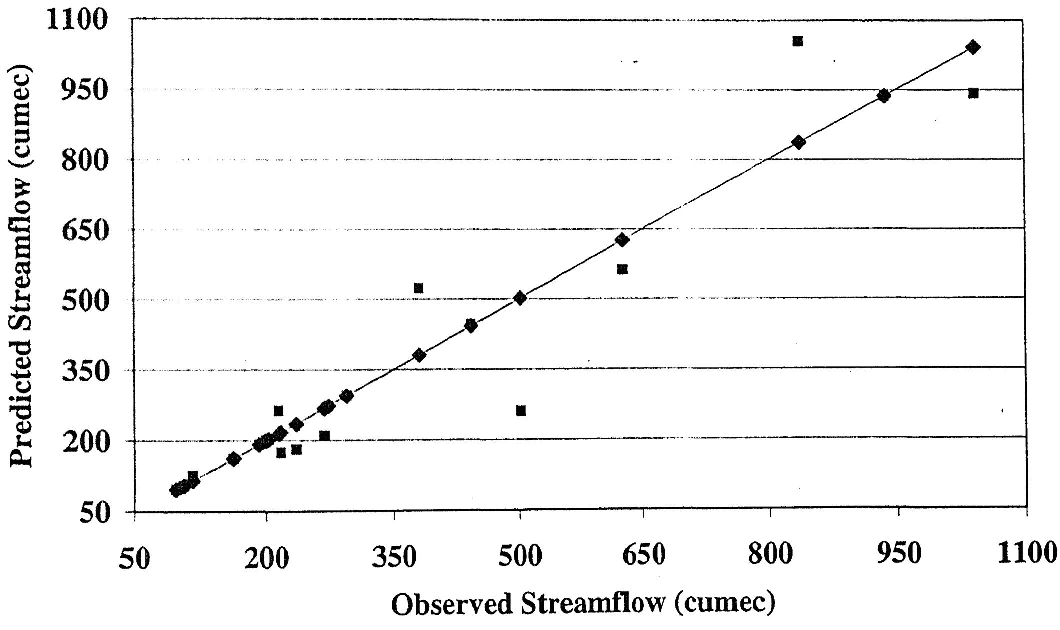


Figure 5.10: UH Model Validation from Category-IV Storms

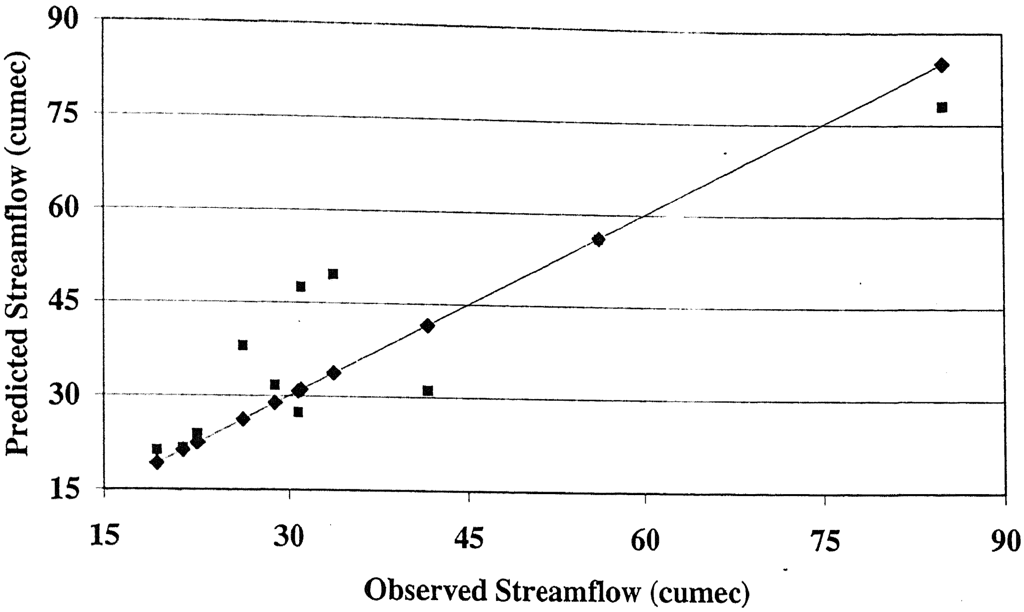


Figure 5.11: Scatter Plot for Category-I storms from ANN 2-5-1 Model During Training

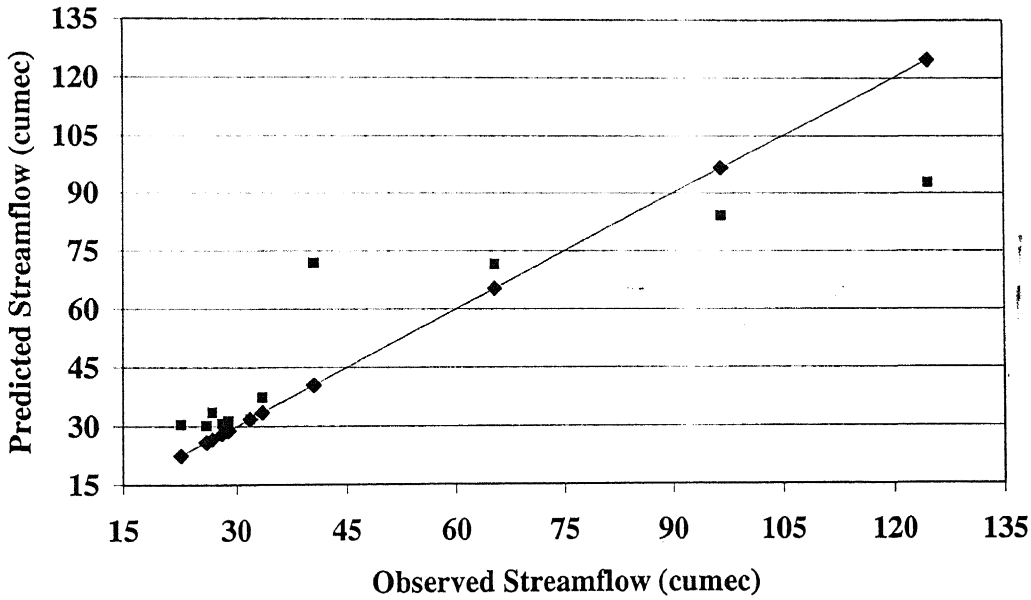


Figure 5.12: Scatter Plot for Category-I storms from ANN 2-5-1 Model During Testing

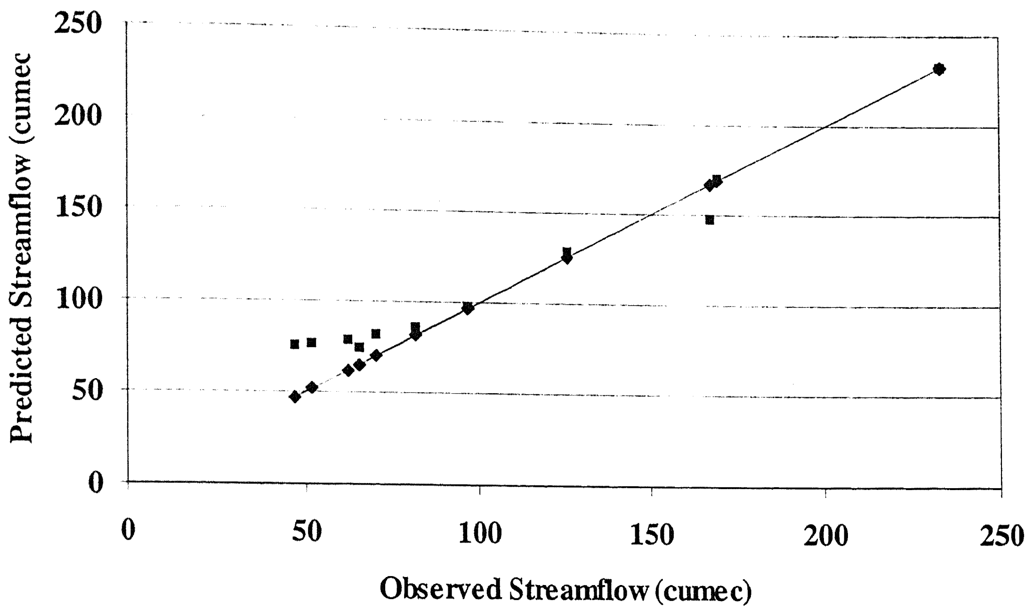


Figure 5.13: Scatter Plot for Category-II storms from ANN 2-6-1 Model During Training

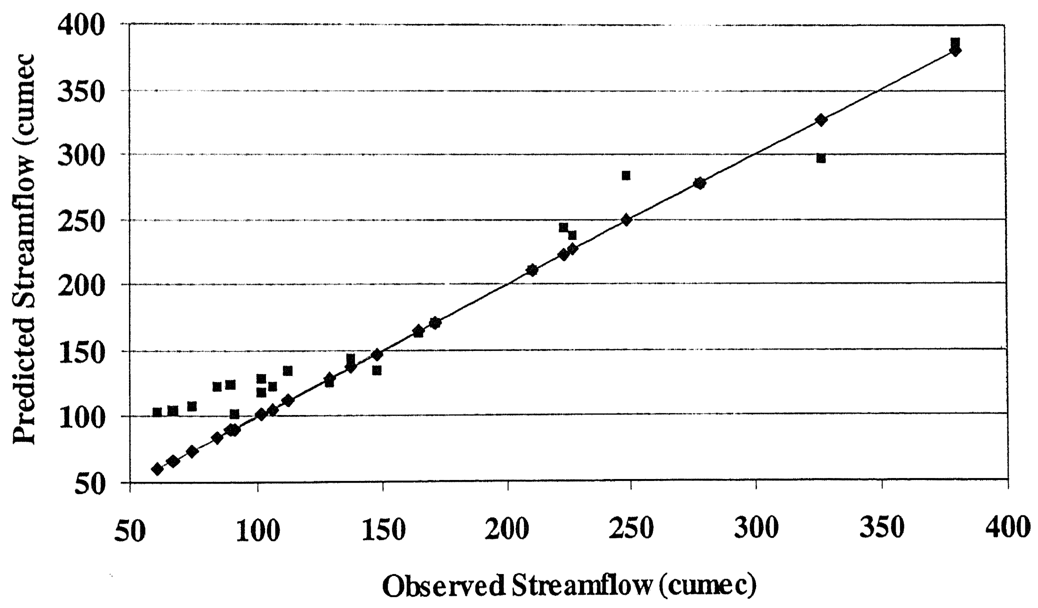


Figure 5.14: Scatter Plot for Category-II storms from ANN 2-6-1 Model During Testing

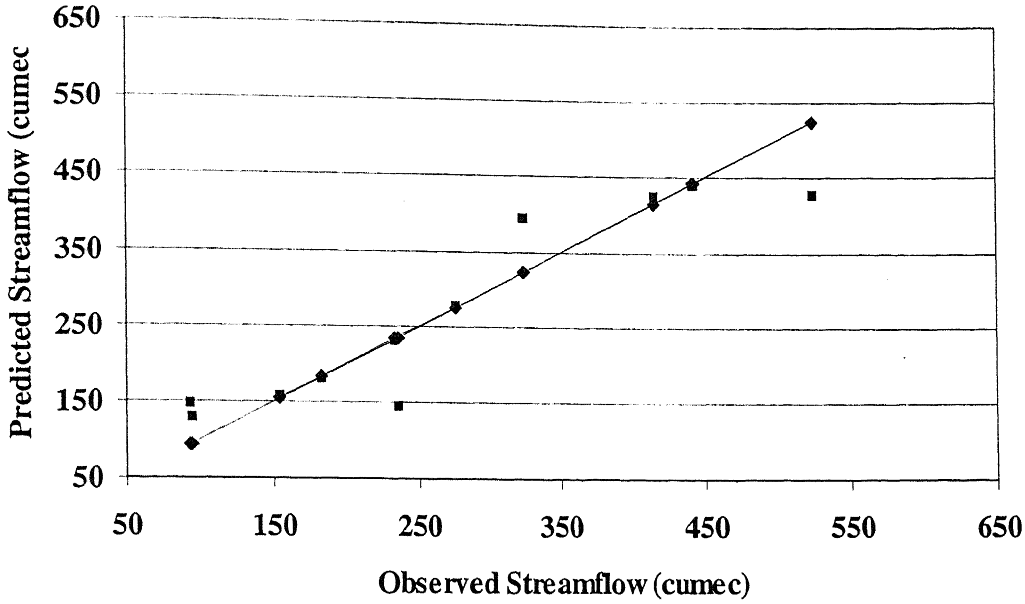


Figure 5.35: Scatter Plot for Category-III storms from ANN 2-10-1 Model During Training

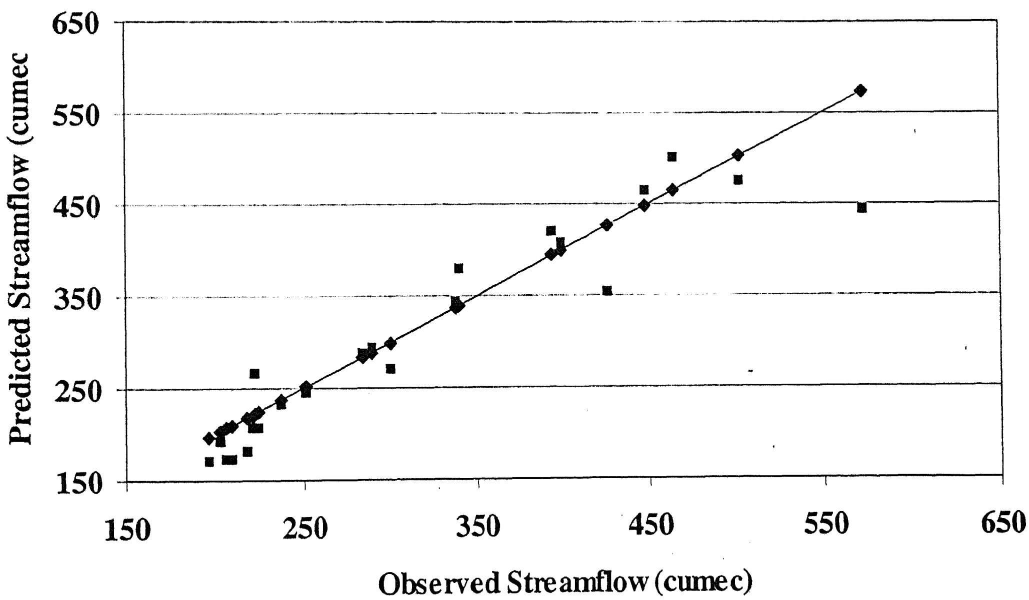


Figure 5.16: Scatter Plot for Category-III storms from ANN 2-10-1 Model During Testing

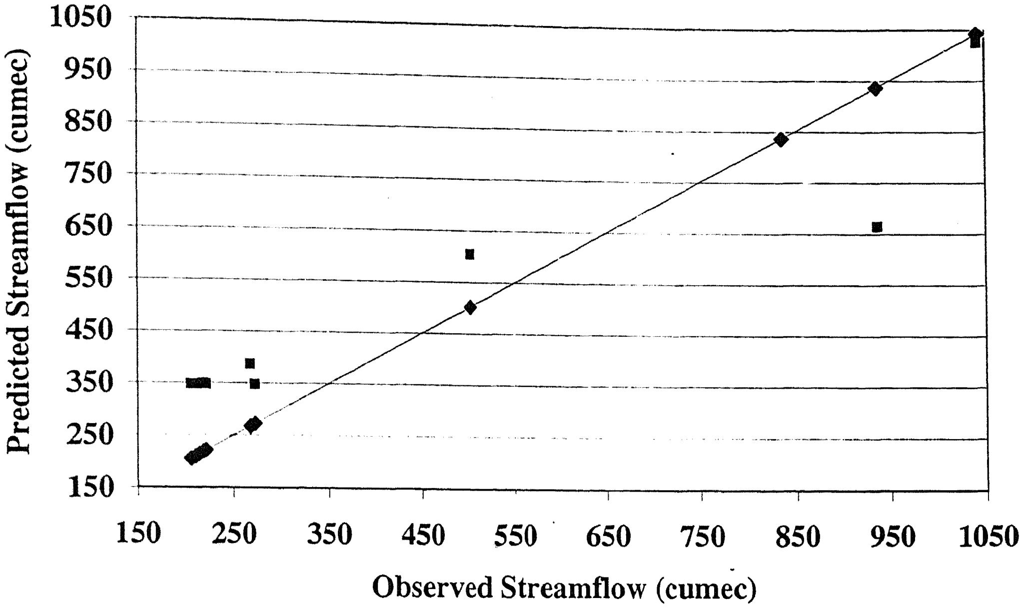


Figure 5.17: Scatter Plot for Category-IV storms from ANN 3-6-1 Model During Training

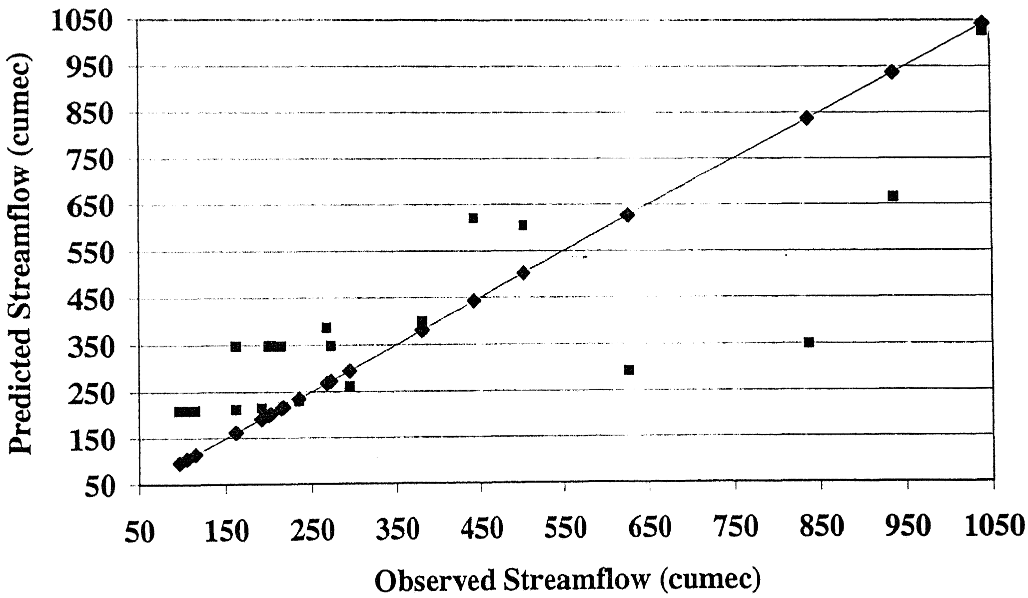


Figure 5.18: Scatter Plot for Category-IV storms from ANN 3-6-1 Model During Testing

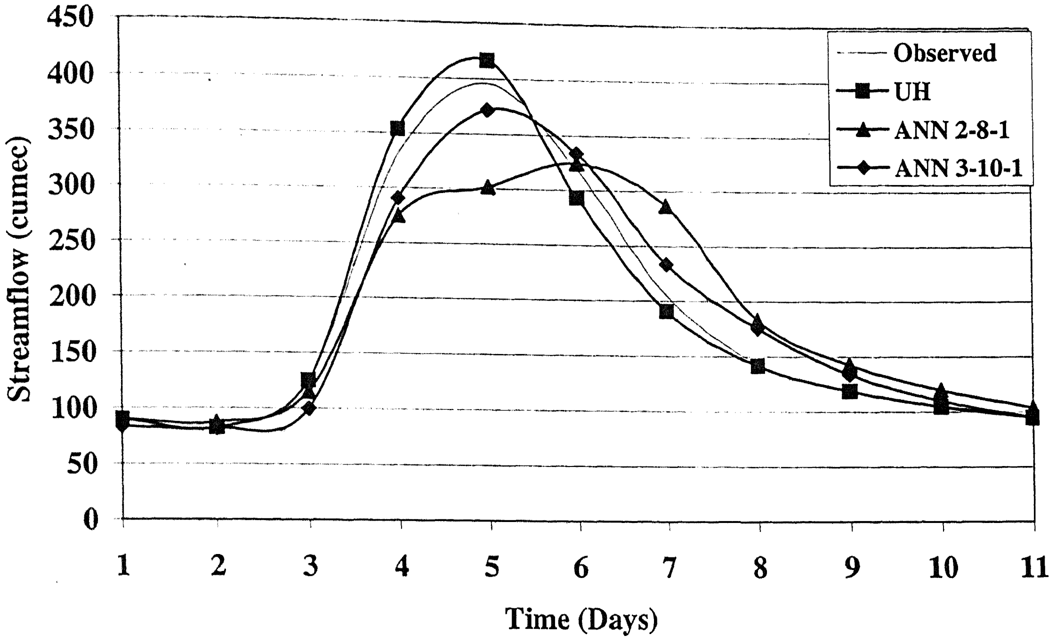


Figure 5.19: During Calibration/Training Combined Input

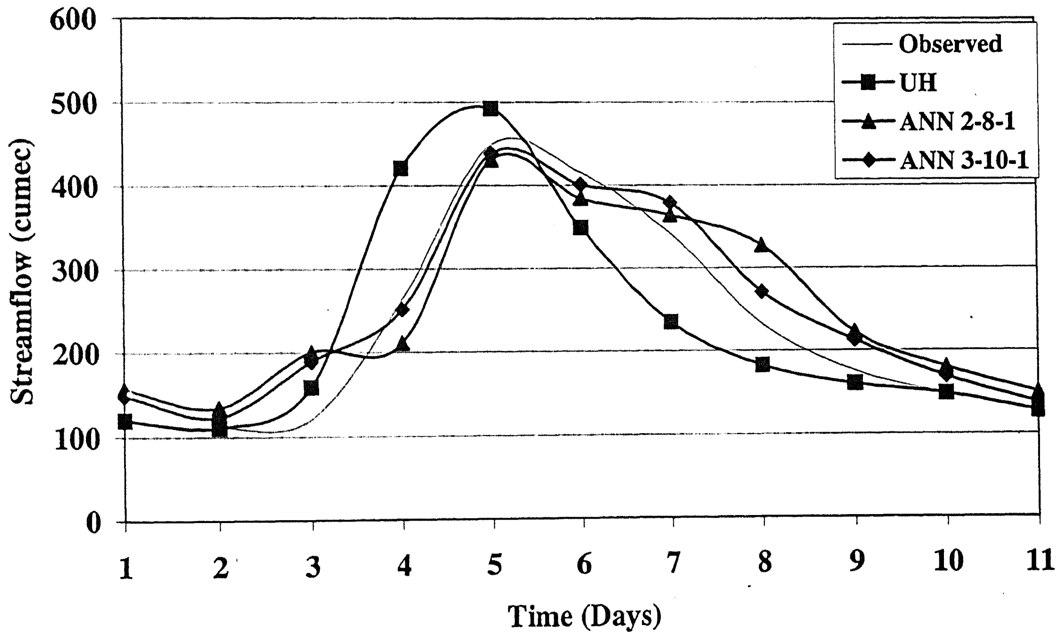


Figure 5.20: During Validation/Testing Combined Input

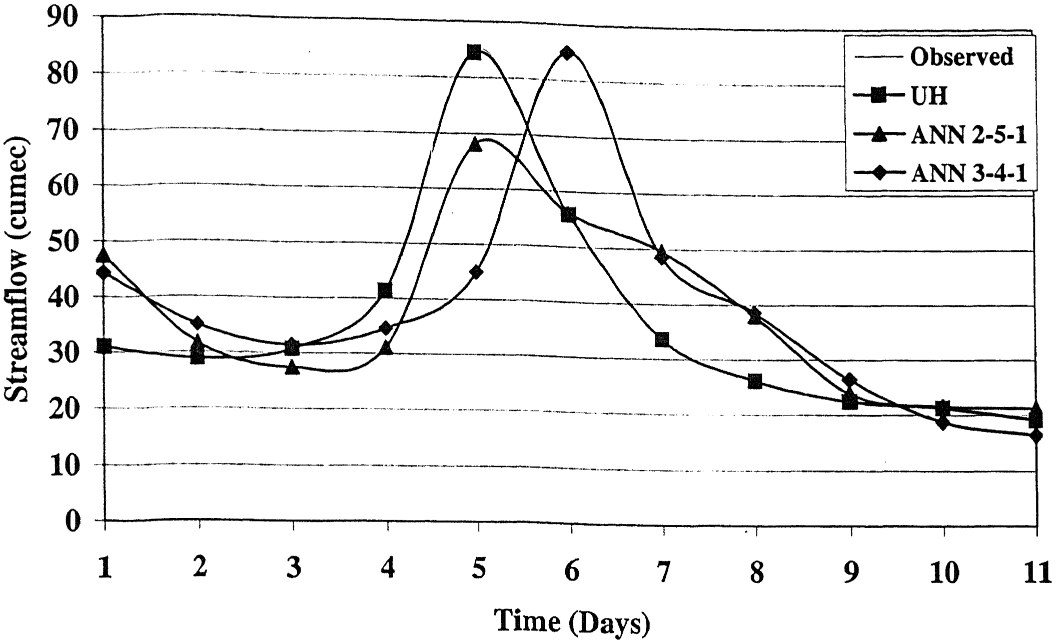


Figure 5.21: Category-I Storm During Calibration/Training

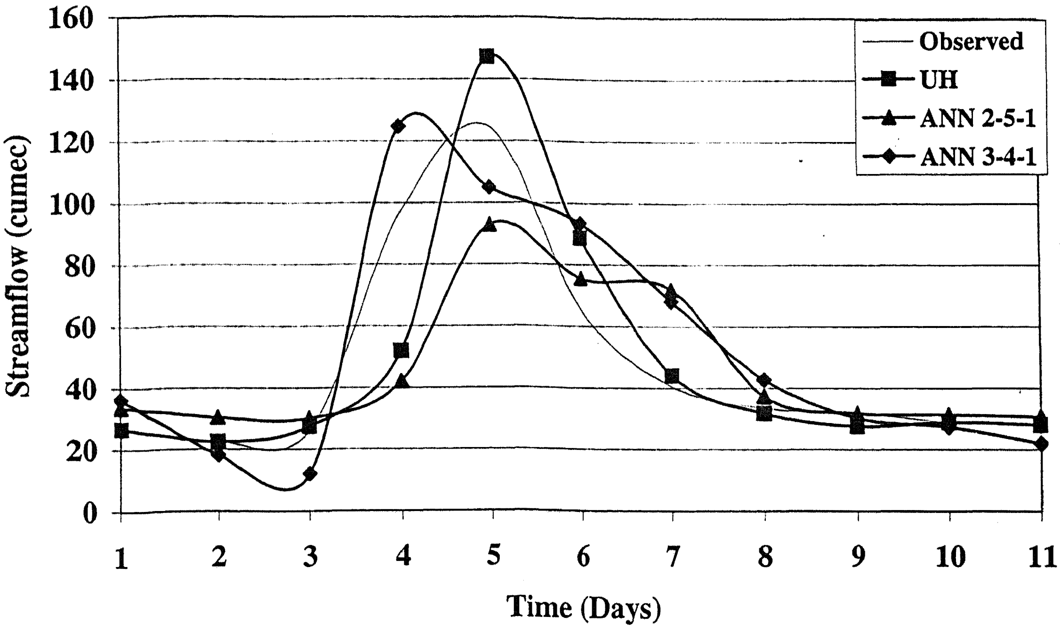


Figure 5.22: Category-I Storm During Validation/Testing

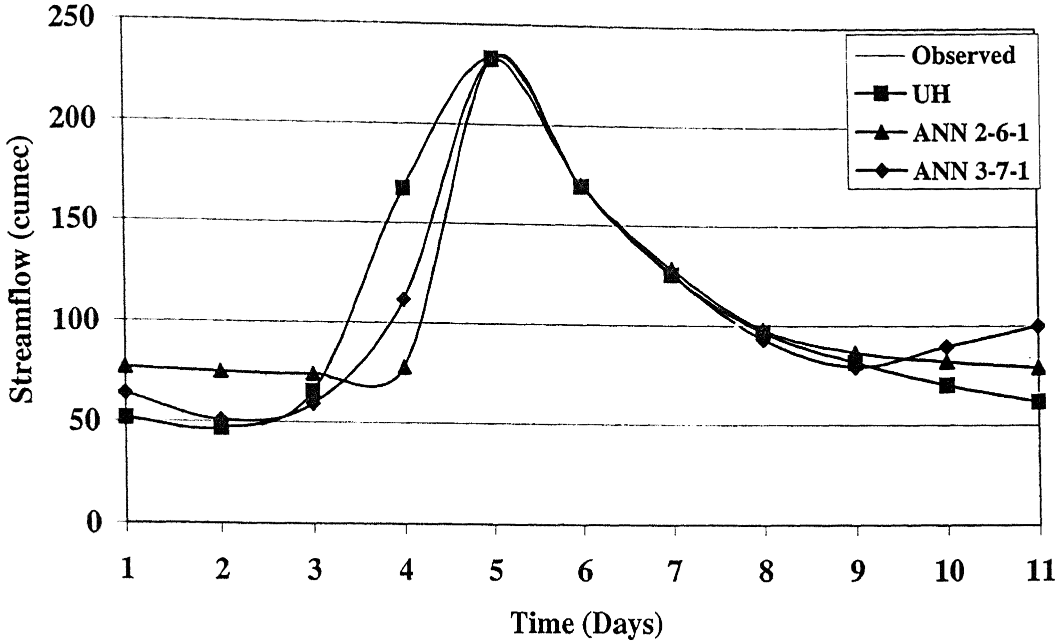


Figure 3.23: Category-II Storm During Calibration/Training

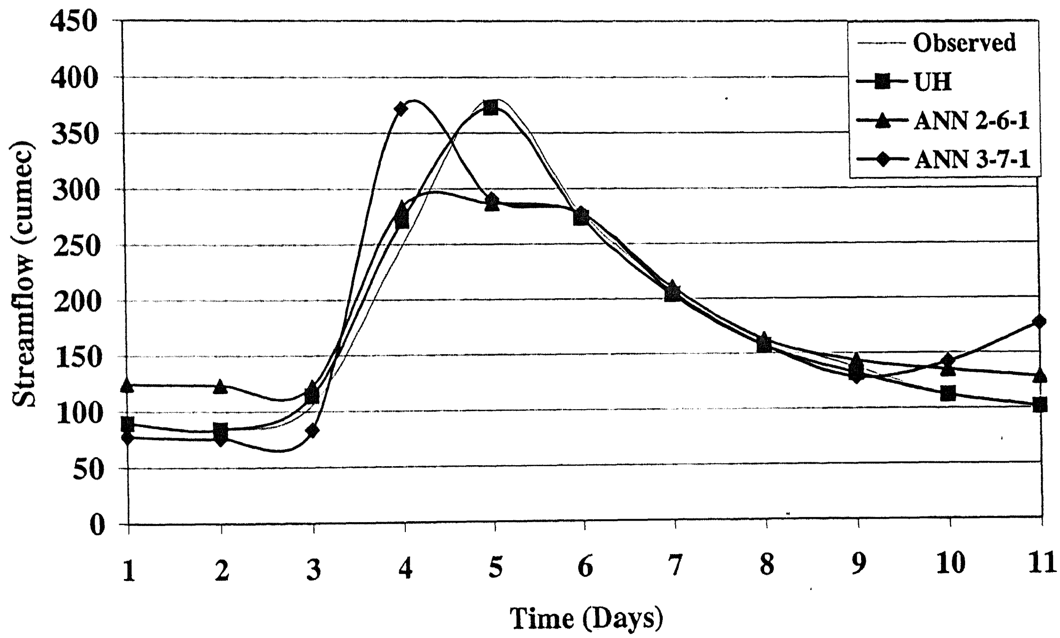


Figure 5.24: Figure 2: Category-II Storm During Validation/Testing

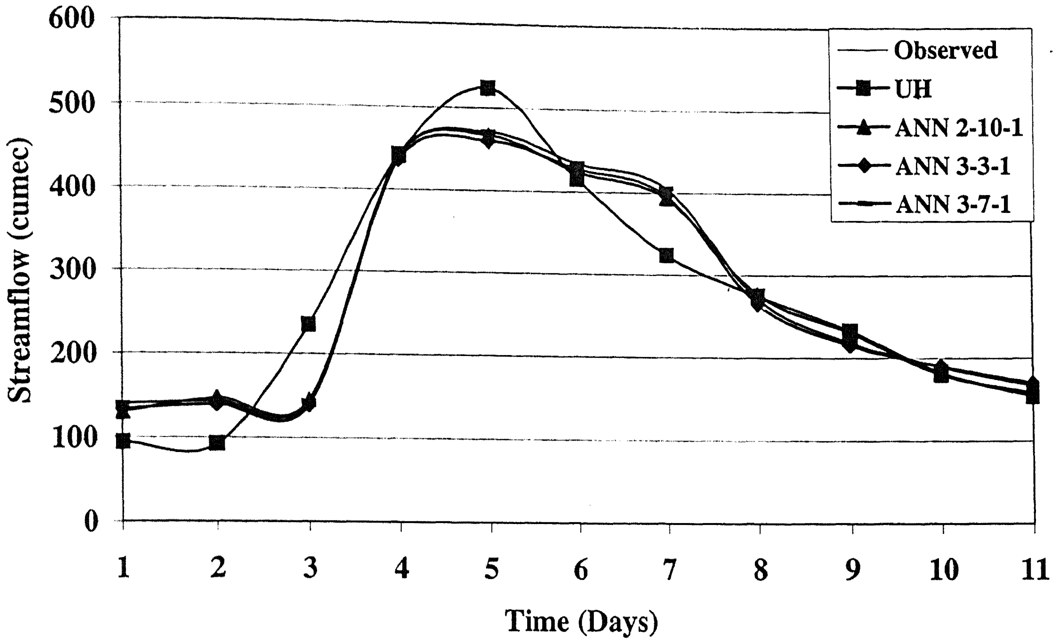


Figure 5.25: Category-III Storm During Calibration/Training

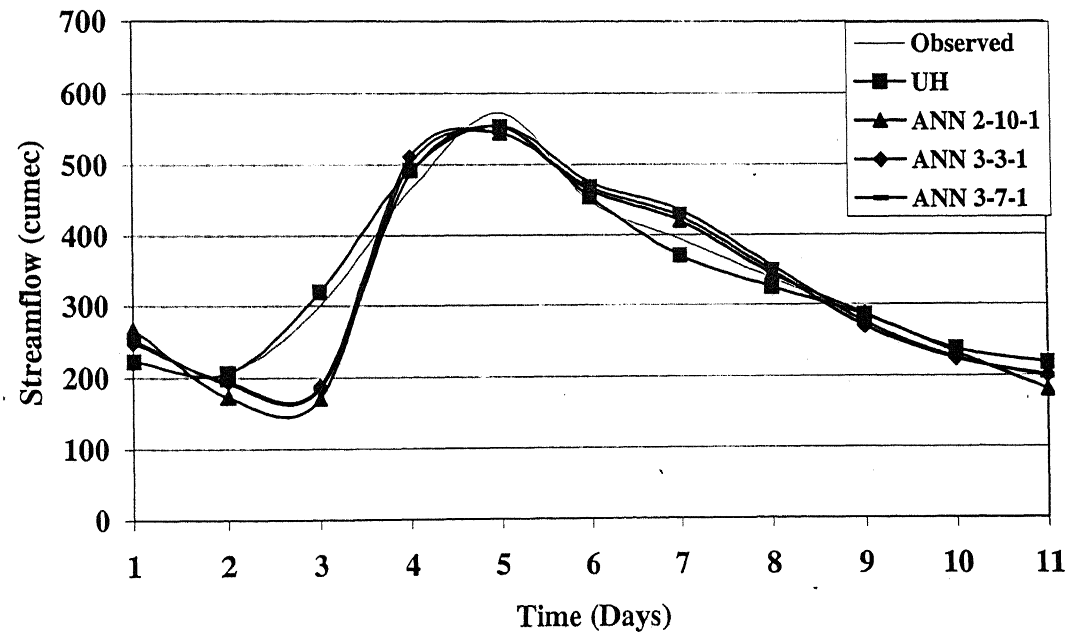


Figure 5.26: Figure 2: Category-III Storm During Validation/Testing

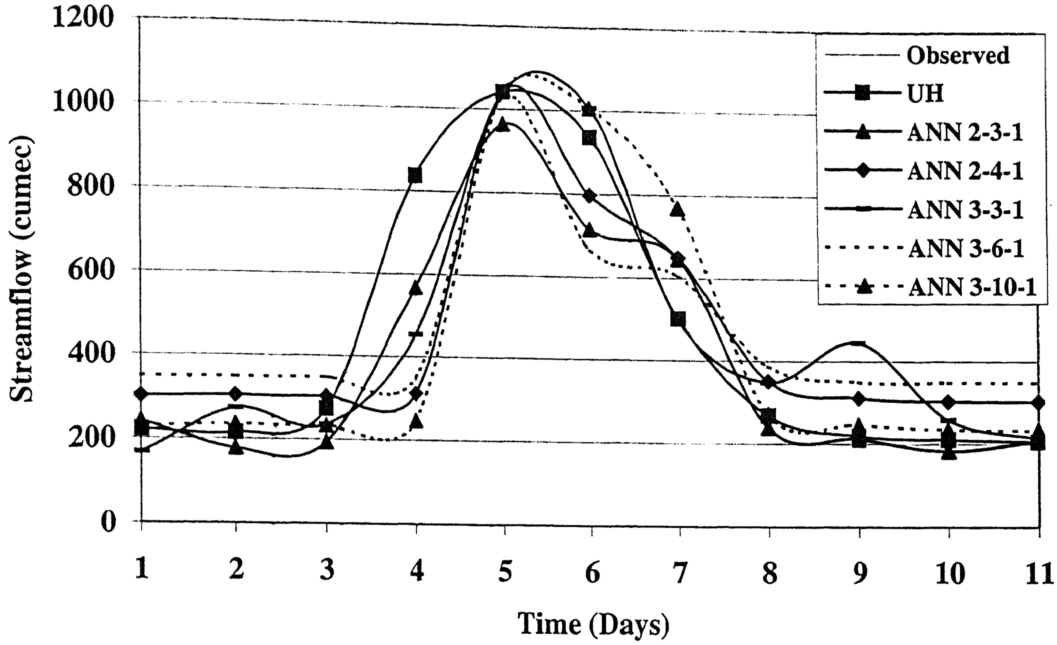


Figure 5.27: Category-IV Storm During Calibration/Training

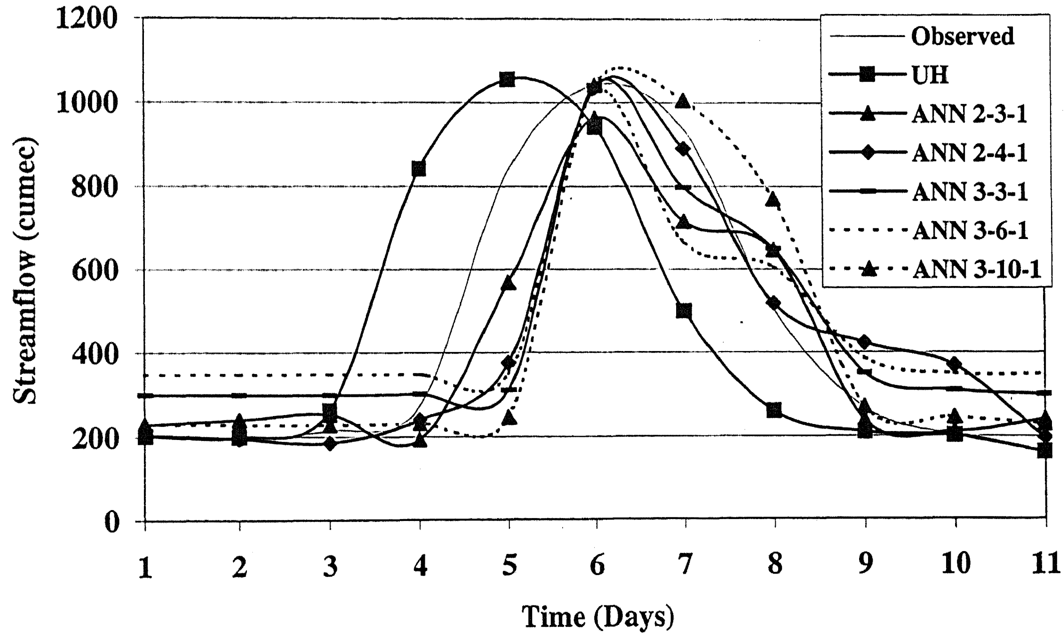


Figure 5.28: Figure 2: Category-IV Storm During Validation/Testing

Chapter 6

Summary, Conclusions, and Scope of Future Work

6.1 Summary

This thesis presents the findings of a study on the evaluation of various techniques available for modeling the event-based rainfall-runoff process. The techniques investigated include conceptual techniques and artificial neural network (ANN) technique. Among the conceptual techniques, four different conceptual rainfall runoff (CRR) model structures were investigated: unit hydrograph (UH), NASH's conceptual hydrograph model, Clark's conceptual hydrograph model, and a non-linear water TANK model. Among the ANN models, two types of ANN models were investigated that differed in the number of input variables considered to model the complex, dynamic, and non-linear event-based rainfall-runoff process. The rainfall and flow data derived from the Kentucky River basin were employed to develop all model structures investigated in the present study. The data considered in this study include spatially averaged daily total rainfall (mm) taken from five different locations scattered throughout the Kentucky River basin, and the daily average flow on Kentucky River near Winchester, Kentucky, USA. The total rainfall and average flow data from thirteen isolated storms were available, which were divided into two sets: a calibration or training set consisting of data from six storms, and a validation or testing set consisting of the data from the remaining storms. The whole data set was also sub-divided into four categories depending upon the peak magnitude in order to test the hypothesis that the models developed using the decomposed data sets based on physical concepts may perform better than the models developed on the whole data set consisting of a wide variation in flow magnitudes and hence more complex rainfall-runoff relationships. An attempt was also made to develop

guidelines to ensure that the developed ANN models are the best models for a given data set while training the various ANN models, and that the developed ANN models are not over-trained or under-trained. A wide variety of standard statistical performance evaluation measures were employed to evaluate the performances of all the model structures investigated.

6.2 Conclusions

The results of the evaluation of various techniques for rainfall-runoff modeling carried out in this study for the case when the data from many storms are combined into one calibration set indicate that the 3-10-1 ANN model was the best in terms of various performance statistics. The UH model performed comparable to the best ANN model during calibration/training, the ANN model performed significantly better than the CRR models during validation/testing. These results strengthen and verify the earlier findings by many researchers that the ANN technique is quite efficient in modeling the complex, dynamic, and non-linear rainfall-runoff process. The massively parallel structure of the ANN models help them in better generalizing the complex rainfall-runoff relationships inherent in a large data set consisting of wide range of flow magnitudes. Since the rainfall-runoff relationships in different magnitude events are different, it is better to rely on a model structure that can not only provide good efficiency in modeling but also good effectiveness in accurately predicting the flow values.

The results of the evaluation of various techniques for rainfall-runoff modeling carried out in this study for the case when the data from many storms are divided into four categories depending on the peak magnitude indicate that the conventional modeling techniques of UH and NASH are more suitable than the other techniques for modeling the event-based rainfall-runoff process in a large watershed. It has been found that (a) the performances of the conceptual models were better than the ANN models, and that the UH model is the most suitable model for modeling the event-based rainfall-runoff process for the data under Category-I; (b) the conceptual models performed better than the ANN models for modeling the event-based rainfall-runoff process under Category-II,

and the UH and NASH models were found to be better than all other models; (c) the UH model was found to be the most suitable model for modeling the event-based rainfall-runoff process for Category-III; the performance of the NASH and 3-3-1 ANN model was the next best; and the performance of the other CRR and ANN models was moderate and comparable to each other; and (d) the UH model is the most suitable model for modeling the event-based rainfall-runoff process for Category-IV; and the performance of the NASH model was the next best in modeling the event-based rainfall-runoff model. In summary, it can be said that when the data are divided into different categories based on peak flow values, the conceptual methods can be preferred over the ANNs and that the UH is still the best method of modeling the event-based rainfall-runoff process. This finding is particularly interesting since the UH method is generally considered applicable for watersheds of areas up to approximately 5000 km^2. However, the drainage area of the Kentucky River considered in this study was more than 10,000 km^2.

In this study, an attempt was made to develop new guidelines for training of various architectures. It has been found that while training the ANN models, the emphasis should be on the evaluation of the models by examining the differences between the training and testing error statistics using a wide variety of performance statistics rather than training the ANN models using the global error at the output layer during training only. An ANN model trained using MSE or similar error statistic during training data set only will tend to be either over-trained or under-trained depending upon its architecture. Further, it has been found that the performance of the ANN model depends upon the level of acceptable global error at the output layer. Instead of using a constant level of acceptable error for every architecture during training, it should be made adaptive and an optimum level of acceptable global error at the output layer should be identified to prevent over-training and/or under-training of the network. Further, the investigation of various error statistics considered in this study indicate that the unbiased error statistics such as average absolute relative error (AARE) are better indicator of the performance of a model than the error statistics normally employed such as MSE and RMSE. This is due to the fact that the error statistics such as MSE and RMSE tend to increase with an increase in the

magnitude of the variable being modeled, and hence get dominated by the high magnitudes of the variables being modeled.

6.3 Scope for Future Work

The author would like to mention that no study is complete and there are always scopes for improvements and further work. In light of the present research work, the following limitations/scope for future works are identified. The conceptual models considered in this study are lumped in nature. The performances of the CRR models can be further improved by considering the spatial variations in the rainfall, runoff, and other hydrologic variables. The infiltration was estimated using the Φ–index method in developing the UH, NASH, and Clarks's models. It would be possible to enhance the performances of these models if infiltration is estimated using more accurate methods such as Green-Ampt method. It was interesting to find the UH and NASH models performing very well in a large watershed such as Kentucky River basin. The suitability of the conceptual techniques such as UH and NASH models must be investigated for modeling the event-based rainfall-runoff process in large watersheds of varying hydrological and climatic conditions. The training of the ANN models was carried out using the back-propagation training algorithm, which does not guarantee the global optimum solution and has been reported to be inefficient. Although an attempt was made to obtain a solution close to the global optimum solution by developing fifteen different ANN models for each architecture investigated having different initial weights, the global solution can never be guaranteed. It would be interesting to employ other training methods that may improve the performance of the ANN models. Finally, the results reported in this study are based on a small data set of thirteen storms only; however, the study was limited due to the availability of the data. Ideally, it would be better to consider a larger data set and data from more watersheds in order to have greater confidence in the findings of such studies. It is hoped that the future research efforts will concentrate on some of these directions to enhance the performance of the event-based rainfall-runoff models and hence the important water resources planning, design, and management activities.

Appendix-A

Performance of Various Models in Terms of Standard Statistical Parameters

Table A-1: Performance Evaluation Criteria from Various Models (Combined Input)

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH	0.9850	0.9701	11.56	37.9	45.5	65.2	89.4	97.0	100.0	0.02	36.28
NASH	0.9814	0.9617	15.82	19.7	37.9	60.6	81.8	92.4	100.0	2.03	41.07
CLARK-1	0.9227	0.8305	29.82	18.2	24.2	30.3	54.6	84.9	95.5	-3.75	86.42
CLARK-2	0.9585	0.8940	22.73	19.7	28.8	28.8	65.2	89.4	100.0	-3.99	68.33
TANK	0.8807	0.6496	178.23	1.5	3.0	10.6	28.8	53.0	69.7	-4.97	124.26
ANN 2-2-1	0.9203	0.8451	119.86	1.5	10.6	22.7	48.5	62.1	74.2	2.66	82.61
ANN 2-3-1	0.9352	0.8739	81.16	1.5	9.1	22.7	51.5	66.7	81.8	2.93	74.54
ANN 2-4-1	0.9283	0.8609	94.74	1.5	16.7	21.2	51.5	68.2	78.8	2.25	78.27
ANN 2-5-1	0.9389	0.8808	83.17	4.6	12.1	21.2	50.0	68.2	81.8	2.44	72.48
ANN 2-6-1	0.9389	0.8812	57.82	4.6	9.1	22.7	48.5	75.8	87.9	1.81	72.35
ANN 2-7-1	0.9004	0.7232	48.25	4.6	6.1	7.6	19.7	51.5	95.5	-22.81	110.43
ANN 2-8-1	**0.9438**	**0.8906**	**55.09**	**1.5**	**15.2**	**24.2**	**53.0**	**77.3**	**87.9**	**0.91**	**69.41**
ANN 2-9-1	0.9366	0.8770	68.05	4.6	18.2	25.8	47.0	69.7	84.9	0.75	73.61
ANN 2-10-1	0.9339	0.8712	84.80	4.6	16.7	28.8	53.0	68.2	80.3	2.03	75.34
ANN 2-11-1	0.9317	0.8526	90.49	3.0	12.1	21.2	50.0	72.7	80.3	-3.77	80.58
ANN 3-3-1	0.9649	0.9266	111.68	1.5	10.6	30.3	51.5	63.6	72.7	5.79	56.88
ANN 3-4-1	0.9665	0.9221	67.62	6.1	16.7	33.3	57.6	69.7	84.9	7.47	58.59
ANN 3-5-1	0.9791	0.9569	51.02	1.5	22.7	33.3	57.6	78.8	87.9	0.25	43.56
ANN 3-6-1	0.9680	0.9365	75.51	4.6	21.2	37.9	59.1	68.2	81.8	1.27	52.91
ANN 3-7-1	0.9621	0.9220	111.53	3.0	16.7	27.3	59.1	69.7	74.2	6.64	58.63
ANN 3-8-1	0.9717	0.9441	57.79	1.5	21.2	37.9	57.6	74.2	86.4	0.66	49.61
ANN3-9-1	0.9500	0.9011	124.67	0.0	18.2	31.8	51.5	66.7	74.2	2.17	66.02
ANN 3-10-1	**0.9837**	**0.9676**	**50.39**	**6.1**	**16.7**	**34.9**	**59.1**	**78.8**	**87.9**	**-0.09**	**37.80**
ANN 3-11-1	0.9277	0.8049	130.39	1.5	4.6	9.1	18.2	43.9	71.2	27.02	92.71

Table A-2: Performance Evaluation Criteria from Various Models (Combined Input)

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Validation/Testing											
UH	0.9611	0.9189	12.54	37.9	42.4	59.1	87.9	97.0	98.5	0.02	40.44
NASH	0.9177	0.6385	28.39	19.7	33.3	57.6	72.7	86.4	92.4	18.44	85.39
CLARK-1	0.8753	0.7225	35.36	18.2	24.2	31.8	63.6	84.9	93.9	11.87	74.82
CLARK-2	0.9227	0.8086	26.96	21.2	30.3	39.4	66.7	87.9	97.0	11.59	62.14
TANK	0.8359	0.5533	77.70	1.5	7.6	13.6	47.0	66.7	74.2	19.32	94.92
ANN 2-2-1	0.8947	0.7986	38.56	4.6	15.2	31.8	59.1	75.8	89.4	-2.86	90.44
ANN 2-3-1	0.9116	0.8305	29.53	6.1	24.2	39.4	59.1	75.8	97.0	-0.75	82.97
ANN 2-4-1	0.9057	0.8191	32.94	4.6	18.2	33.3	60.6	77.3	95.5	-1.45	85.73
ANN 2-5-1	0.9137	0.8345	29.93	3.0	18.2	40.9	56.1	77.3	97.0	-1.22	81.99
ANN 2-6-1	0.9123	0.8314	25.54	0.0	13.6	24.2	57.6	84.9	100.0	1.06	82.75
ANN 2-7-1	0.8570	0.5445	50.18	1.5	1.5	1.5	16.7	50.0	95.5	-21.53	136.02
ANN 2-8-1	**0.9099**	**0.8263**	**26.91**	**4.6**	**12.1**	**34.9**	**59.1**	**84.9**	**95.5**	**0.81**	**83.99**
ANN 2-9-1	0.9122	0.8320	25.86	6.1	15.2	34.9	56.1	84.9	98.5	-1.00	82.61
ANN 2-10-1	0.9011	0.8111	36.44	4.6	22.7	37.9	62.1	77.3	92.4	-1.12	87.59
ANN 2-11-1	0.8779	0.7598	34.43	3.0	24.2	36.4	57.6	78.8	92.4	-7.52	98.78
ANN 3-3-1	0.9472	0.8972	30.29	6.1	18.2	36.4	69.7	84.9	89.4	-0.50	64.63
ANN 3-4-1	0.9430	0.8758	27.80	3.0	24.2	42.4	65.2	84.9	95.5	3.42	71.04
ANN 3-5-1	0.9611	0.9214	21.67	4.6	27.3	42.4	69.7	90.9	97.0	-2.47	56.49
ANN 3-6-1	0.9487	0.8983	27.56	7.6	27.3	40.9	66.7	80.3	93.9	-3.43	64.27
ANN 3-7-1	0.9308	0.8657	38.13	4.6	21.2	31.8	65.2	78.8	86.4	-0.48	73.85
ANN 3-8-1	0.9479	0.8964	24.44	4.6	24.2	39.4	66.7	89.4	95.5	-2.33	64.87
ANN3-9-1	0.9307	0.8593	37.34	1.5	15.2	36.4	60.6	78.8	87.9	-6.77	75.60
ANN 3-10-1	**0.9610**	**0.9233**	**21.00**	**7.6**	**25.8**	**40.9**	**69.7**	**90.9**	**100.0**	**0.00**	**55.82**
ANN 3-11-1	0.9135	0.7426	57.03	3.0	6.1	10.6	24.2	59.1	83.3	25.42	102.25

Table A-3: Performance Evaluation Criteria from Various Models: Category I

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.8779	0.8707	7.03	27.3	63.6	72.7	90.9	100.0	100.0	-0.08	6.62
CLARK-1	0.8160	0.6395	16.19	18.2	18.2	45.5	81.8	90.9	100.0	-0.50	11.27
CLARK-2	0.8530	0.7028	14.95	18.2	27.3	36.4	81.8	100.0	100.0	-0.73	10.24
TANK	0.8461	0.5884	24.69	0.0	0.0	27.3	54.6	90.9	100.0	-30.92	17.58
ANN 2-2-1	0.7333	0.4546	23.63	9.1	9.1	27.3	54.6	100.0	100.0	-0.77	15.36
ANN 2-3-1	0.6852	0.3718	37.63	0.0	0.0	9.1	36.4	81.8	100.0	12.90	16.24
ANN 2-4-1	0.7737	0.7389	23.77	9.1	18.2	18.2	63.6	100.0	100.0	-0.29	14.39
ANN 2-5-1	**0.7988**	**0.7709**	**23.02**	**9.1**	**18.2**	**36.4**	**54.6**	**90.9**	**100.0**	**-0.01**	**14.01**
ANN 2-6-1	0.6922	0.4118	19.58	9.1	18.2	27.3	72.7	90.9	100.0	-8.32	15.82
ANN 2-7-1	0.7316	0.4354	28.58	0.0	9.1	9.1	54.6	100.0	100.0	6.92	16.62
ANN 2-8-1	0.7709	0.4352	25.75	0.0	0.0	27.3	54.6	81.8	100.0	5.11	15.57
ANN 2-9-1	0.8214	0.5842	25.17	0.0	9.1	27.3	54.6	90.9	100.0	3.33	13.85
ANN 2-10-1	0.7195	0.3313	36.46	0.0	0.0	18.2	45.5	81.8	90.9	15.08	20.01
ANN 2-11-1	0.5636	0.3209	53.33	9.1	9.1	18.2	27.3	36.4	100.0	59.47	30.26
ANN 3-3-1	0.7853	0.5536	22.65	9.1	27.3	36.4	63.6	100.0	100.0	0.06	14.22
ANN 3-4-1	**0.8276**	**0.6175**	**28.77**	**0.0**	**9.1**	**9.1**	**54.6**	**90.9**	**100.0**	**7.06**	**16.80**
ANN 3-5-1	0.7948	0.5655	22.75	18.2	18.2	36.4	63.6	100.0	100.0	0.13	14.08
ANN 3-6-1	0.7821	0.5138	22.96	0.0	18.2	18.2	45.5	90.9	100.0	-2.64	15.03
ANN 3-7-1	0.7964	0.5897	31.06	9.1	9.1	18.2	45.5	81.8	100.0	3.37	16.06
ANN 3-8-1	0.7205	0.3424	27.40	0.0	9.1	18.2	54.6	90.9	100.0	8.20	16.55
ANN3-9-1	0.6988	0.4531	21.52	0.0	18.2	27.3	63.6	100.0	100.0	-1.85	14.23
ANN 3-10-1	0.7318	0.2829	35.84	0.0	9.1	18.2	36.4	81.8	100.0	18.74	17.15
ANN 3-11-1	0.7687	0.7329	102.87	0.0	0.0	9.1	18.2	27.3	45.5	68.54	29.59

Table A-4: Performance Evaluation Criteria from Various Models: Category I

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Validation/Testing											
UH	0.8871	0.7302	12.12	36.4	36.4	63.6	81.8	100.0	100.0	0.06	16.75
NASH	0.8461	0.8451	21.08	18.2	36.4	45.5	54.6	72.7	90.9	38.36	29.12
CLARK-1	0.7860	0.5800	30.27	18.2	27.3	36.4	45.5	72.7	90.9	37.32	29.20
CLARK-2	0.8660	0.6399	38.78	18.2	18.2	18.2	36.4	72.7	90.9	36.76	21.87
TANK	0.8389	0.5177	65.41	0.0	9.1	9.1	27.3	45.5	72.7	44.20	30.46
ANN 2-2-1	0.7393	0.4809	29.22	0.0	9.1	9.1	54.6	81.8	100.0	-8.06	26.38
ANN 2-3-1	0.7054	0.3955	58.69	0.0	0.0	0.0	0.0	36.4	100.0	16.59	28.01
ANN 2-4-1	0.7558	0.6779	30.15	0.0	0.0	18.2	36.4	81.8	100.0	-9.59	19.67
ANN 2-5-1	**0.8022**	**0.7506**	**26.61**	**9.1**	**9.1**	**36.4**	**54.6**	**81.8**	**100.0**	**-7.73**	**24.97**
ANN 2-6-1	0.6896	0.3938	33.73	0.0	0.0	9.1	54.6	90.9	100.0	-16.33	32.94
ANN 2-7-1	0.6441	0.4598	30.28	0.0	0.0	0.0	36.4	81.8	100.0	-7.30	20.14
ANN 2-8-1	0.7819	0.3663	41.63	0.0	0.0	0.0	45.5	63.6	100.0	8.78	31.98
ANN 2-9-1	0.7949	0.5618	39.03	0.0	0.0	9.1	45.5	72.7	90.9	-9.72	38.31
ANN 2-10-1	0.6726	0.5150	48.28	0.0	9.1	9.1	36.4	63.6	90.9	-1.61	37.67
ANN 2-11-1	0.5694	0.3731	44.96	0.0	9.1	18.2	36.4	63.6	100.0	56.20	48.08
ANN 3-3-1	0.6703	0.5468	27.75	0.0	18.2	27.3	63.6	81.8	100.0	-6.55	18.90
ANN 3-4-1	**0.7304**	**0.5821**	**31.32**	**0.0**	**9.1**	**18.2**	**36.4**	**81.8**	**100.0**	**5.88**	**20.85**
ANN 3-5-1	0.6936	0.5059	36.12	0.0	0.0	0.0	9.1	9.1	90.9	10.74	27.55
ANN 3-6-1	0.7704	0.5036	32.56	0.0	9.1	9.1	36.4	81.8	100.0	-5.78	25.11
ANN 3-7-1	0.7793	0.5452	48.29	0.0	9.1	9.1	18.2	54.6	100.0	14.84	21.98
ANN 3-8-1	0.7384	0.4183	30.51	9.1	9.1	18.2	45.5	72.7	100.0	-5.19	27.58
ANN3-9-1	0.6318	0.3664	34.24	0.0	9.1	27.3	36.4	63.6	100.0	-22.92	34.07
ANN 3-10-1	0.5704	0.2427	38.64	0.0	0.0	0.0	45.5	63.6	100.0	-15.08	30.71
ANN 3-11-1	0.5813	0.6971	110.04	0.0	0.0	0.0	9.1	18.2	54.6	57.07	40.11

Table A-5: Performance Evaluation Criteria from Various Models: Category II

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9648	0.9650	7.20	27.3	54.6	81.8	90.9	100.0	100.0	5.53	10.75
CLARK-1	0.8280	0.6268	28.89	18.2	36.4	45.5	54.6	90.9	90.9	18.49	35.13
CLARK-2	0.9740	0.8341	20.96	18.2	27.3	36.4	45.5	100.0	100.0	18.05	23.42
TANK	0.8849	0.7049	19.18	0.0	27.3	45.5	63.6	100.0	100.0	-3.21	31.24
ANN 2-2-1	0.8599	0.6619	18.85	9.1	27.3	45.5	72.7	90.9	100.0	-0.13	26.24
ANN 2-3-1	0.8197	0.5867	23.28	9.1	18.2	45.5	63.6	72.7	100.0	-1.11	30.61
ANN 2-4-1	0.8213	0.5939	20.09	9.1	27.3	54.6	63.6	81.8	100.0	-1.20	30.22
ANN 2-5-1	0.8433	0.6326	20.70	27.3	36.4	36.4	63.6	90.9	100.0	-0.02	28.02
ANN 2-6-1	**0.8722**	**0.7426**	**20.90**	**18.2**	**36.4**	**45.5**	**63.6**	**81.8**	**100.0**	**0.87**	**30.10**
ANN 2-7-1	0.8258	0.6011	18.57	9.1	45.5	54.6	63.6	90.9	100.0	-1.91	29.82
ANN 2-8-1	0.8339	0.5546	22.49	36.4	36.4	54.6	54.6	81.8	100.0	1.81	29.06
ANN 2-9-1	0.8553	0.6077	20.17	27.3	36.4	54.6	63.6	90.9	100.0	-0.57	23.17
ANN 2-10-1	0.8729	0.7296	23.11	9.1	45.5	45.5	54.6	81.8	100.0	-0.10	28.20
ANN 2-11-1	0.8373	0.6203	23.08	27.3	36.4	45.5	54.6	90.9	100.0	1.90	28.74
ANN 3-3-1	0.8270	0.6042	19.46	18.2	45.5	54.6	63.6	90.9	100.0	-0.40	29.65
ANN 3-4-1	0.8480	0.6062	21.00	18.2	27.3	45.5	63.6	90.9	100.0	0.05	29.53
ANN 3-5-1	0.8334	0.6145	20.23	9.1	45.5	45.5	63.6	90.9	100.0	-1.62	29.07
ANN 3-6-1	0.8241	0.5993	18.44	18.2	45.5	54.6	63.6	90.9	100.0	-0.95	29.92
ANN 3-7-1	**0.8898**	**0.7146**	**16.46**	**27.3**	**45.5**	**63.6**	**72.7**	**90.9**	**100.0**	**1.15**	**22.67**
ANN 3-8-1	0.8360	0.6198	21.90	18.2	36.4	45.5	54.6	90.9	100.0	0.07	28.76
ANN3-9-1	0.8246	0.5985	22.08	27.3	36.4	36.4	63.6	72.7	100.0	1.39	29.96
ANN 3-10-1	0.8284	0.6049	17.70	27.3	36.4	54.6	63.6	90.9	100.0	-2.15	29.61
ANN 3-11-1	0.8197	0.5858	21.62	9.1	36.4	36.4	63.6	81.8	100.0	-4.20	30.66

Table A-6: Performance Evaluation Criteria from Various Models: Category II

STORM	MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Validation/Testing												
	UH	0.9585	0.8942	12.29	36.4	36.4	45.5	90.9	100.0	100.0	-0.11	10.49
II	NASH	0.9770	0.9425	8.18	18.2	36.4	81.8	90.9	100.0	100.0	-1.53	21.80
	CLARK-1	0.8400	0.6666	21.24	18.2	18.2	45.5	72.7	90.9	100.0	-3.75	52.48
	CLARK-2	0.9540	0.8254	13.35	27.3	36.4	45.5	72.7	100.0	100.0	-4.03	37.98
	TANK	0.8765	0.6499	22.50	9.1	27.3	36.4	54.6	100.0	100.0	-22.87	60.99
	ANN 2-2-1	0.7872	0.5651	22.59	18.2	27.3	45.5	63.6	72.7	100.0	0.99	76.32
	ANN 2-3-1	0.7580	0.4652	26.39	0.0	18.2	36.4	54.6	72.7	100.0	1.96	76.31
	ANN 2-4-1	0.8007	0.5216	22.98	0.0	18.2	36.4	63.6	81.8	100.0	2.35	73.19
	ANN 2-5-1	0.7779	0.6001	24.07	9.1	18.2	36.4	54.6	81.8	100.0	1.80	76.59
	ANN 2-6-1	**0.8517**	**0.7225**	**19.90**	**27.3**	**36.4**	**36.4**	**63.6**	**90.9**	**100.0**	**-0.74**	**62.61**
	ANN 2-7-1	0.7685	0.5551	22.50	0.0	27.3	45.5	63.6	81.8	100.0	0.91	76.86
	ANN 2-8-1	0.7484	0.5266	27.08	9.1	27.3	36.4	45.5	81.8	100.0	4.06	78.37
	ANN 2-9-1	0.7967	0.5277	24.67	9.1	27.3	45.5	63.6	72.7	100.0	0.74	78.31
	ANN 2-10-1	0.8514	0.6932	21.06	9.1	36.4	54.6	54.6	90.9	100.0	-3.79	60.76
	ANN 2-11-1	0.8347	0.6049	24.88	9.1	36.4	45.5	45.5	81.8	100.0	3.12	68.33
	ANN 3-3-1	0.7936	0.5563	49.18	0.0	0.0	9.1	36.4	54.6	90.9	19.65	79.44
	ANN 3-4-1	0.8246	0.5061	44.21	0.0	0.0	0.0	27.3	63.6	100.0	23.86	82.00
	ANN 3-5-1	0.7555	0.5395	50.60	9.1	9.1	9.1	36.4	36.4	90.9	2.64	95.74
	ANN 3-6-1	0.8243	0.6732	20.98	27.3	27.3	45.5	63.6	81.8	100.0	2.92	71.39
	ANN 3-7-1	**0.8312**	**0.7047**	**23.25**	**9.1**	**27.3**	**45.5**	**63.6**	**90.9**	**100.0**	**-1.21**	**73.02**
	ANN 3-8-1	0.7869	0.6381	24.66	18.2	36.4	45.5	45.5	81.8	100.0	3.36	75.06
	ANN3-9-1	0.8087	0.7074	24.38	0.0	27.3	36.4	45.5	90.9	100.0	3.09	71.15
	ANN 3-10-1	0.8052	0.6618	20.49	9.1	45.5	45.5	63.6	81.8	100.0	1.54	73.75
	ANN 3-11-1	0.6925	0.4637	26.70	0.0	9.1	18.2	54.6	81.8	100.0	-2.87	84.11

Table A-7: Performance Evaluation Criteria from Various Models: Category III

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9891	0.9739	5.89	27.3	54.6	86.4	95.5	100.0	100.0	-0.12	18.59
CLARK-1	0.8230	0.6282	20.86	22.8	22.8	27.3	63.6	95.5	100.0	-4.54	74.19
CLARK-2	0.9390	0.8098	16.19	18.2	27.3	36.4	77.3	100.0	100.0	-4.84	53.47
CLARK-7	0.9350	0.8103	18.92	22.8	31.9	50.1	63.7	86.4	100.0	12.19	52.02
TANK	0.8974	0.6895	21.52	4.6	27.3	45.5	68.2	90.9	100.0	-8.88	66.81
ANN 2-2-1	0.9203	0.8469	18.72	9.1	36.4	54.6	72.7	90.9	100.0	0.01	53.35
ANN 2-3-1	0.9233	0.8502	15.09	18.2	36.4	54.6	81.8	100.0	100.0	-1.68	52.78
ANN 2-4-1	0.9207	0.8476	18.49	18.2	36.4	54.6	72.7	90.9	100.0	0.03	53.23
ANN 2-5-1	0.9269	0.8591	17.86	9.1	45.5	45.5	72.7	90.9	100.0	-0.06	51.17
ANN 2-6-1	0.9219	0.8500	18.56	9.1	27.3	45.5	72.7	90.9	100.0	-0.14	52.81
ANN 2-7-1	0.9271	0.8593	17.94	18.2	36.4	54.6	63.6	90.9	100.0	-0.21	51.14
ANN 2-8-1	0.9098	0.8199	22.19	9.1	27.3	45.5	72.7	81.8	100.0	3.41	57.87
ANN 2-9-1	0.9214	0.8429	19.42	9.1	18.2	45.5	72.7	100.0	100.0	2.05	54.05
ANN 2-10-1	**0.9333**	**0.8699**	**16.54**	**27.3**	**54.6**	**54.6**	**72.7**	**90.9**	**100.0**	**-0.63**	**49.18**
ANN 2-11-1	0.9317	0.8680	17.62	18.2	36.4	45.5	72.7	90.9	100.0	0.01	49.53
ANN 3-3-1	**0.8634**	**0.7368**	**20.25**	**13.7**	**31.9**	**45.5**	**68.2**	**86.4**	**100.0**	**-0.73**	**60.73**
ANN 3-4-1	0.8361	0.6428	26.11	9.1	13.7	22.8	59.1	86.4	100.0	8.01	69.23
ANN 3-5-1	0.8463	0.6656	19.10	9.1	22.8	45.5	68.2	90.9	100.0	-7.46	66.23
ANN 3-6-1	0.8458	0.6708	27.24	4.6	27.3	31.9	50.0	86.4	100.0	5.35	68.31
ANN 3-7-1	**0.8806**	**0.7637**	**20.40**	**13.7**	**41.0**	**59.1**	**68.2**	**86.4**	**100.0**	**0.38**	**58.23**
ANN 3-8-1	0.8472	0.6685	25.34	9.1	22.8	27.3	54.6	90.9	100.0	6.43	64.68
ANN3-9-1	0.8462	0.6672	25.44	9.1	18.2	31.9	54.6	90.9	100.0	6.11	64.93
ANN 3-10-1	0.8446	0.6642	25.99	9.1	13.7	27.3	50.0	86.4	100.0	6.27	65.49
ANN 3-11-1	0.8387	0.6495	26.41	4.6	13.7	27.3	54.6	86.4	100.0	7.47	68.12

Table A-8: Performance Evaluation Criteria from Various Models: Category III

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Validation/Testing											
UH	0.9902	0.9790	3.08	41.0	68.2	100.0	100.0	100.0	100.0	0.01	15.40
NASH	0.9698	0.9420	14.58	18.2	36.4	50.1	77.3	100.0	100.0	16.71	40.22
CLARK-1	0.7790	0.5718	19.01	22.8	27.3	41.0	72.8	95.5	100.0	12.12	70.09
CLARK-2	0.9565	0.7925	13.81	22.8	31.9	50.1	81.8	100.0	100.0	11.82	49.22
CLARK-7	0.9095	0.8169	28.94	18.2	18.2	18.2	45.5	81.8	100.0	29.17	56.65
TANK	0.8669	0.5962	19.27	0.0	22.8	27.3	68.2	95.5	100.0	-12.93	74.37
ANN 2-2-1	0.8820	0.7380	12.75	9.1	9.1	54.6	90.9	100.0	100.0	-4.25	58.89
ANN 2-3-1	0.8796	0.7308	12.94	9.1	9.1	54.6	90.9	100.0	100.0	-4.09	59.70
ANN 2-4-1	0.8798	0.7323	12.81	9.1	18.2	54.6	90.9	100.0	100.0	-4.38	59.53
ANN 2-5-1	0.8692	0.7040	12.50	9.1	36.4	45.5	90.9	100.0	100.0	-5.14	62.60
ANN 2-6-1	0.8880	0.7541	11.97	0.0	9.1	72.7	90.9	100.0	100.0	-3.47	57.06
ANN 2-7-1	0.8968	0.7732	11.40	0.0	27.3	63.6	90.9	100.0	100.0	-5.60	54.79
ANN 2-8-1	0.8505	0.6307	14.46	0.0	27.3	36.4	90.9	100.0	100.0	-4.20	69.92
ANN 2-9-1	0.8661	0.6921	13.22	0.0	27.3	54.6	90.9	100.0	100.0	-3.41	63.84
ANN 2-10-1	**0.8898**	**0.7774**	**12.91**	**0.0**	**36.4**	**54.6**	**90.9**	**100.0**	**100.0**	**-5.37**	**60.08**
ANN 2-11-1	0.8633	0.6760	13.87	18.2	27.3	45.5	90.9	100.0	100.0	-6.35	65.50
ANN 3-3-1	**0.8610**	**0.6681**	**9.63**	**0.0**	**45.5**	**81.8**	**90.9**	**95.5**	**100.0**	**-7.00**	**62.33**
ANN 3-4-1	0.8284	0.5993	11.82	4.6	31.9	63.6	81.8	100.0	100.0	-0.84	68.58
ANN 3-5-1	0.7835	0.1575	22.52	0.0	18.2	22.8	63.7	90.9	100.0	-15.67	96.52
ANN 3-6-1	0.8277	0.6410	11.59	9.1	45.5	54.6	86.4	100.0	100.0	-4.08	66.45
ANN 3-7-1	**0.8666**	**0.6549**	**14.18**	**4.6**	**13.7**	**40.9**	**90.9**	**95.5**	**100.0**	**-10.84**	**69.92**
ANN 3-8-1	0.8474	0.6496	11.12	4.6	45.5	68.2	86.4	100.0	100.0	-1.61	62.88
ANN3-9-1	0.8473	0.6423	11.45	4.6	36.4	68.2	86.4	100.0	100.0	-2.16	63.78
ANN 3-10-1	0.8528	0.6421	11.37	9.1	31.9	68.2	86.4	100.0	100.0	-3.26	63.81
ANN 3-11-1	0.8377	0.6080	12.61	4.6	27.3	63.6	86.4	100.0	100.0	-1.18	67.66

Table A-9: Performance Evaluation Criteria from Various Models: Category IV

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Calibration/Training											
UH											
NASH	0.9793	0.9709	8.09	27.3	63.6	63.6	90.9	100.0	100.0	0.11	53.52
CLARK-1	0.5710	0.1234	42.29	18.2	18.2	18.2	36.4	36.4	100.0	-23.15	194.30
CLARK-2	0.6610	0.1810	39.50	18.2	27.3	27.3	36.4	45.5	100.0	-23.26	184.46
CLARK-7	0.8730	0.2661	23.77	18.2	27.3	45.5	63.6	81.8	100.0	-36.33	193.24
TANK	0.8045	0.4887	39.77	0.0	18.2	27.3	45.5	63.6	100.0	-11.87	124.37
ANN 2-2-1	0.7854	0.4826	33.34	9.1	18.2	27.3	36.4	72.7	100.0	3.19	82.25
ANN 2-3-1	**0.8163**	**0.5954**	**27.75**	**9.1**	**9.1**	**27.3**	**63.6**	**90.9**	**90.9**	**-5.70**	**48.71**
ANN 2-4-1	**0.7843**	**0.4821**	**32.64**	**9.1**	**9.1**	**9.1**	**27.3**	**90.9**	**100.0**	**0.90**	**82.38**
ANN 2-5-1	0.6930	0.3677	32.38	0.0	0.0	18.2	27.3	90.9	100.0	-12.80	111.01
ANN 2-6-1	0.6825	0.4763	36.48	9.1	9.1	9.1	36.4	63.6	100.0	2.94	83.94
ANN 2-7-1	0.9035	0.3490	68.44	18.2	18.2	18.2	18.2	36.4	54.6	26.08	115.34
ANN 2-8-1	0.6431	0.2006	59.91	9.1	9.1	18.2	18.2	36.4	90.9	10.16	146.94
ANN 2-9-1	0.6527	0.2971	35.51	0.0	0.0	9.1	27.3	90.9	100.0	-14.57	126.89
ANN 2-10-1	0.5548	0.1140	40.47	0.0	18.2	18.2	27.3	54.6	100.0	-39.67	163.64
ANN 2-11-1	0.5076	0.2104	83.61	0.0	9.1	9.1	18.2	36.4	54.6	31.60	144.99
ANN 3-3-1	**0.7636**	**0.7677**	**25.36**	**18.2**	**27.3**	**36.4**	**63.6**	**90.9**	**90.9**	**0.26**	**66.13**
ANN 3-4-1	0.8281	0.4415	68.42	9.1	9.1	9.1	18.2	27.3	100.0	30.83	173.74
ANN 3-5-1	0.6820	0.4869	39.58	0.0	0.0	18.2	36.4	45.5	100.0	-3.06	119.21
ANN 3-6-1	**0.8572**	**0.5709**	**45.08**	**0.0**	**9.1**	**9.1**	**18.2**	**45.5**	**100.0**	**3.97**	**123.22**
ANN 3-7-1	0.7721	0.5971	30.35	0.0	9.1	18.2	36.4	90.9	100.0	-5.65	116.60
ANN 3-8-1	0.8009	0.5597	27.67	9.1	18.2	18.2	36.4	72.7	100.0	-1.13	99.79
ANN3-9-1	0.7677	0.4813	41.70	9.1	18.2	18.2	27.3	45.5	100.0	10.74	120.63
ANN 3-10-1	**0.7759**	**0.3741**	**17.86**	**9.1**	**27.3**	**45.5**	**81.8**	**81.8**	**100.0**	**-3.73**	**122.42**
ANN 3-11-1	0.6031	0.3378	46.08	9.1	9.1	9.1	9.1	63.6	100.0	-27.77	174.48

Table A-10: Performance Evaluation Criteria from Various Models: Category IV

MODEL	R	E	AARE	TS1	TS5	TS10	TS25	TS50	TS100	NMBE	RMSE
During Validation/Testing											
UH	0.9490	0.8926	9.17	45.5	54.6	63.6	90.9	100.0	100.0	0.00	51.52
NASH	0.9716	0.8922	17.62	18.2	45.5	45.5	81.8	90.9	100.0	16.40	61.67
CLARK-1	0.4710	0.1065	35.34	18.2	18.2	18.2	27.3	63.6	100.0	-12.35	148.62
CLARK-2	0.5930	0.2001	29.71	18.2	18.2	27.3	45.5	72.7	100.0	-12.50	140.63
CLARK-7	0.8780	0.2672	42.02	27.3	27.3	27.3	27.3	81.8	90.9	-35.84	134.59
TANK	0.8913	0.5523	49.36	0.0	0.0	9.1	36.4	54.6	81.8	-19.66	105.20
ANN 2-2-1	0.6972	0.4120	47.71	0.0	0.0	0.0	18.2	63.6	100.0	-5.24	103.90
ANN 2-3-1	**0.7281**	**0.4618**	**63.33**	**0.0**	**0.0**	**0.0**	**9.1**	**54.6**	**72.7**	**1.95**	**99.84**
ANN 2-4-1	**0.7824**	**0.6631**	**35.48**	**0.0**	**9.1**	**18.2**	**45.5**	**63.6**	**100.0**	**2.43**	**82.20**
ANN 2-5-1	0.5513	0.2551	37.30	9.1	18.2	18.2	54.6	54.6	100.0	-22.61	116.02
ANN 2-6-1	0.5325	0.4324	45.11	0.0	9.1	9.1	36.4	63.6	90.9	-1.32	102.25
ANN 2-7-1	0.6587	0.3533	68.48	0.0	0.0	9.1	27.3	54.6	72.7	25.59	108.54
ANN 2-8-1	0.5702	0.2066	95.63	0.0	0.0	0.0	0.0	36.4	72.7	0.52	138.46
ANN 2-9-1	0.6068	0.3469	40.27	9.1	9.1	9.1	45.5	63.6	100.0	-12.57	109.04
ANN 2-10-1	0.3939	0.2312	45.58	0.0	0.0	9.1	36.4	54.6	100.0	-47.20	169.63
ANN 2-11-1	0.3762	0.2154	84.66	0.0	0.0	0.0	9.1	18.2	63.6	7.54	159.50
ANN 3-3-1	**0.7411**	**0.5041**	**42.36**	**0.0**	**0.0**	**9.1**	**27.3**	**54.6**	**100.0**	**-19.05**	**109.89**
ANN 3-4-1	0.7819	0.2640	62.21	0.0	0.0	0.0	27.3	54.6	72.7	31.95	91.16
ANN 3-5-1	0.5521	0.3831	51.36	0.0	0.0	18.2	27.3	54.6	90.9	-16.34	130.18
ANN 3-6-1	**0.6828**	**0.5059**	**41.36**	**9.1**	**18.2**	**27.3**	**45.5**	**63.6**	**81.8**	**7.43**	**78.13**
ANN 3-7-1	0.7719	0.5016	33.44	0.0	9.1	18.2	45.5	63.6	100.0	-5.63	78.55
ANN 3-8-1	0.7097	0.4962	23.80	0.0	9.1	36.4	63.6	81.8	100.0	-14.20	88.31
ANN3-9-1	0.6257	0.4439	40.94	0.0	18.2	18.2	27.3	63.6	100.0	-3.68	92.91
ANN 3-10-1	**0.7312**	**0.3591**	**32.65**	**0.0**	**0.0**	**9.1**	**36.4**	**81.8**	**100.0**	**-8.02**	**109.49**
ANN 3-11-1	0.4591	0.2268	69.36	0.0	0.0	0.0	0.0	27.3	90.9	-8.38	175.50

Appendix-B

Performance of Various Models-Scatter Plots

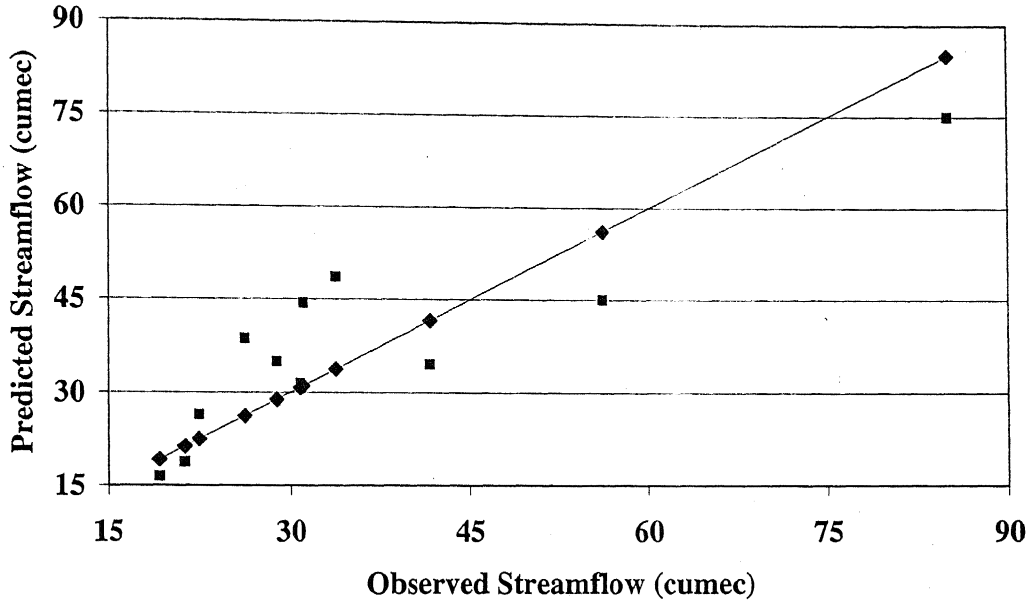


Figure B-1: Scatter Plot for Category-I storms from ANN 3-4-1 Model During Training

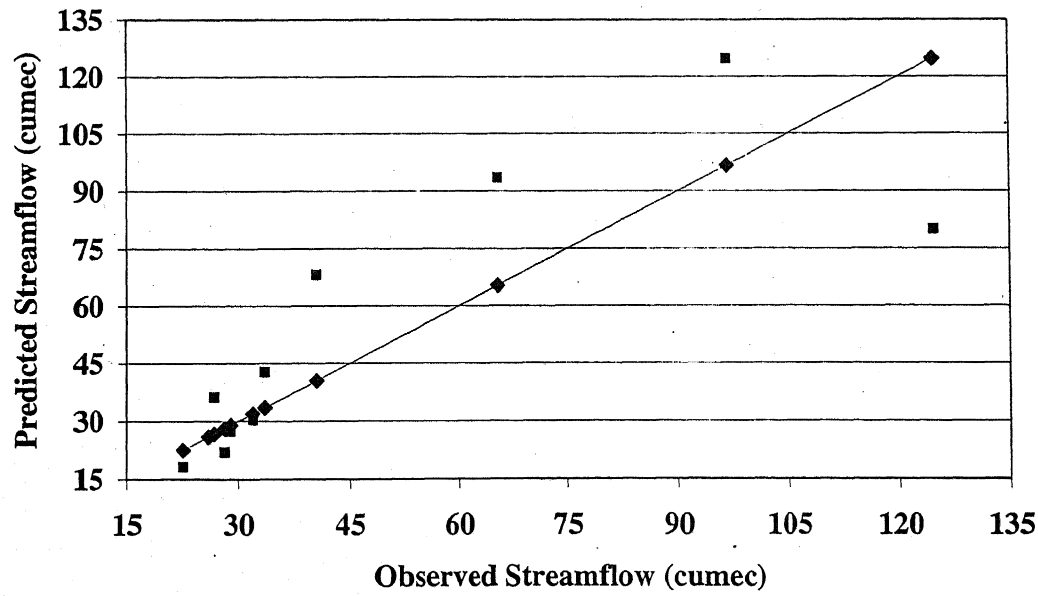


Figure B-2: Scatter Plot for Category-I storms from ANN 3-4-1 Model During Testing

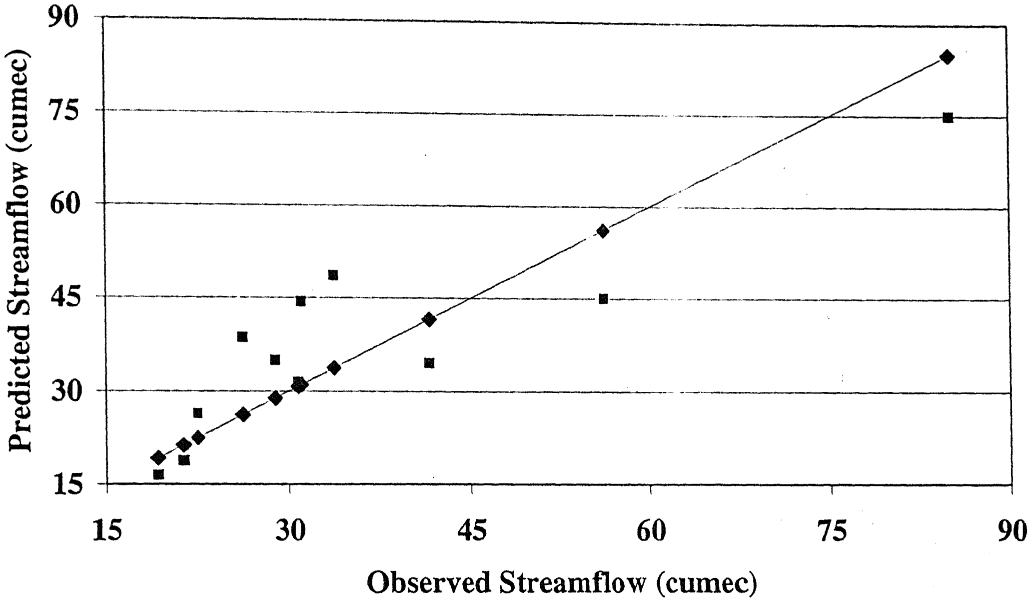


Figure B-1: Scatter Plot for Category-I storms from ANN 3-4-1 Model During Training

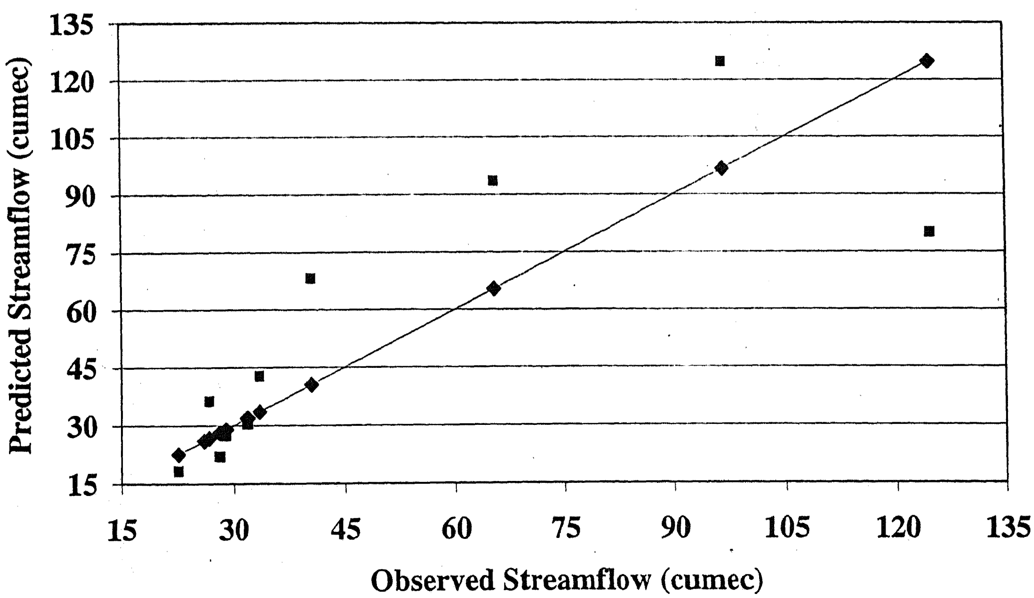


Figure B-2: Scatter Plot for Category-I storms from ANN 3-4-1 Model During Testing

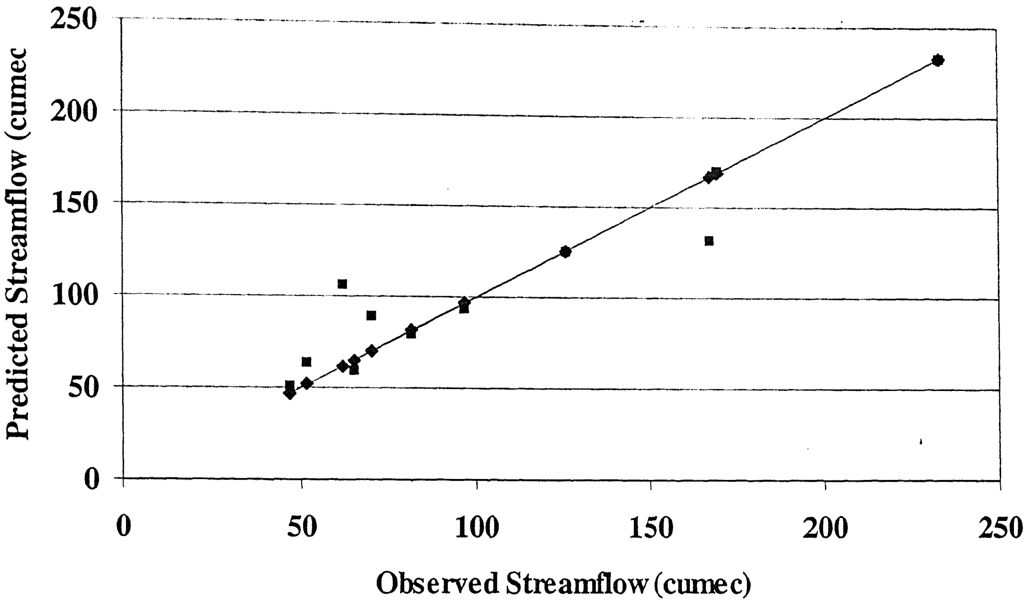
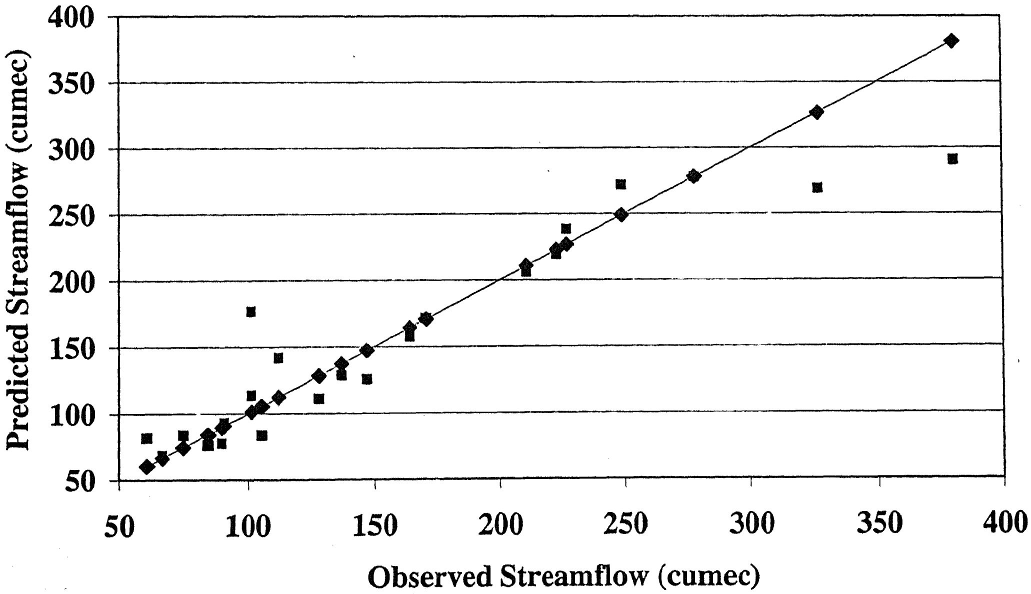


Figure B-3: Scatter Plot for Category-II storms from ANN 3-7-1 Model During Training



FigureB-4: Scatter Plot for Category-II storms from ANN 3-7-1 Model During Testing

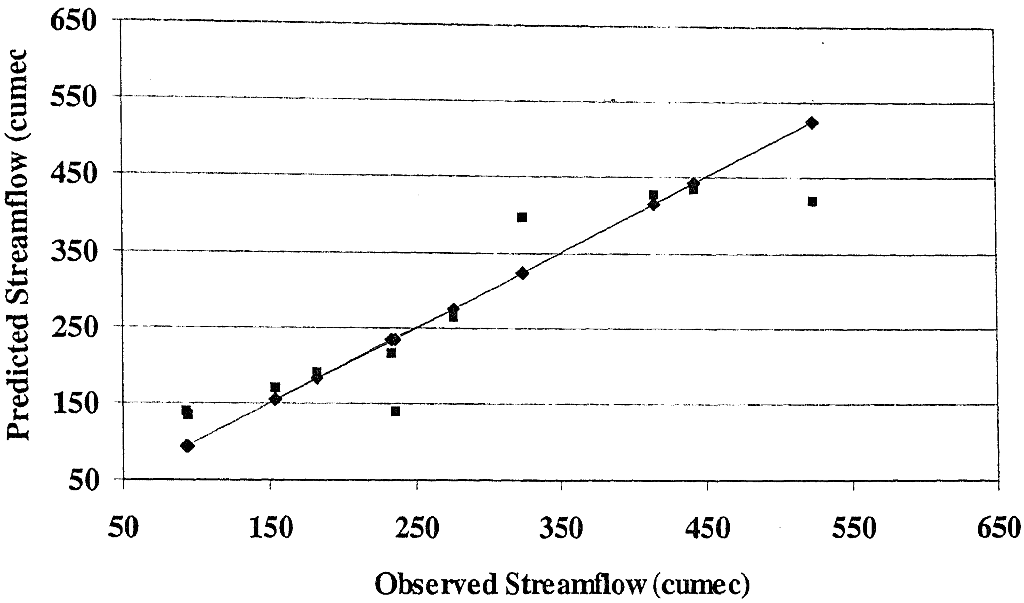


Figure B-5: Scatter Plot for Category-III storms from ANN 3-3-1 Model During Training

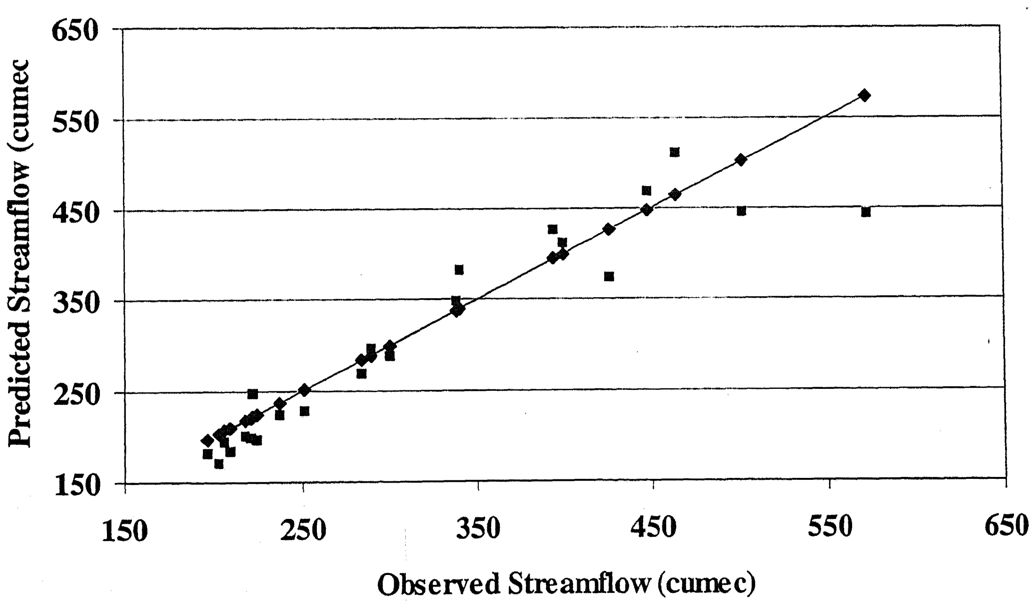


Figure B-6: Scatter Plot for Category-III storms from ANN 3-3-1 Model During Testing

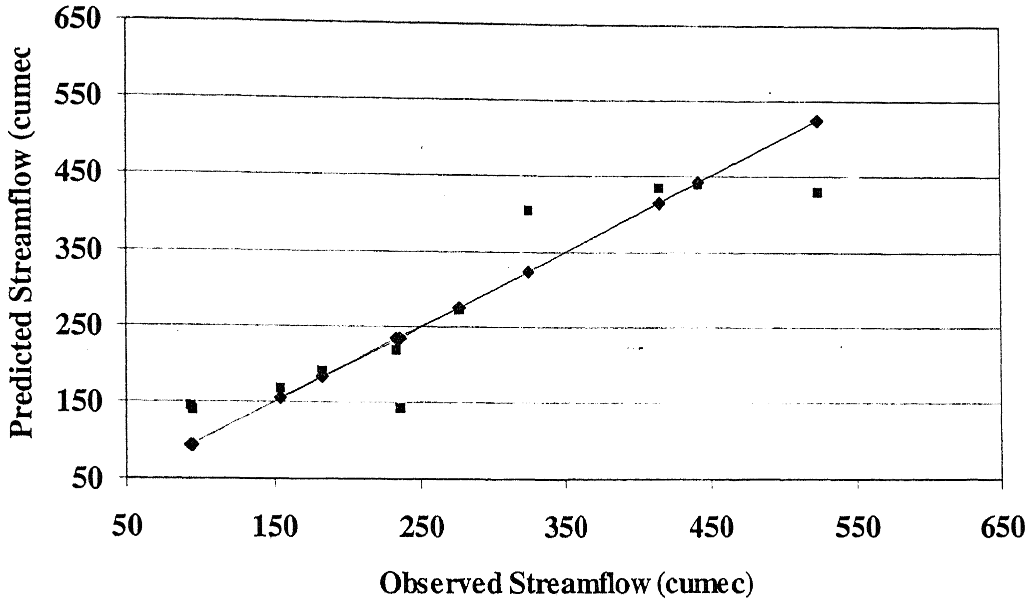


Figure B-7: Scatter Plot for Category-III storms from ANN 3-7-1 Model During Training

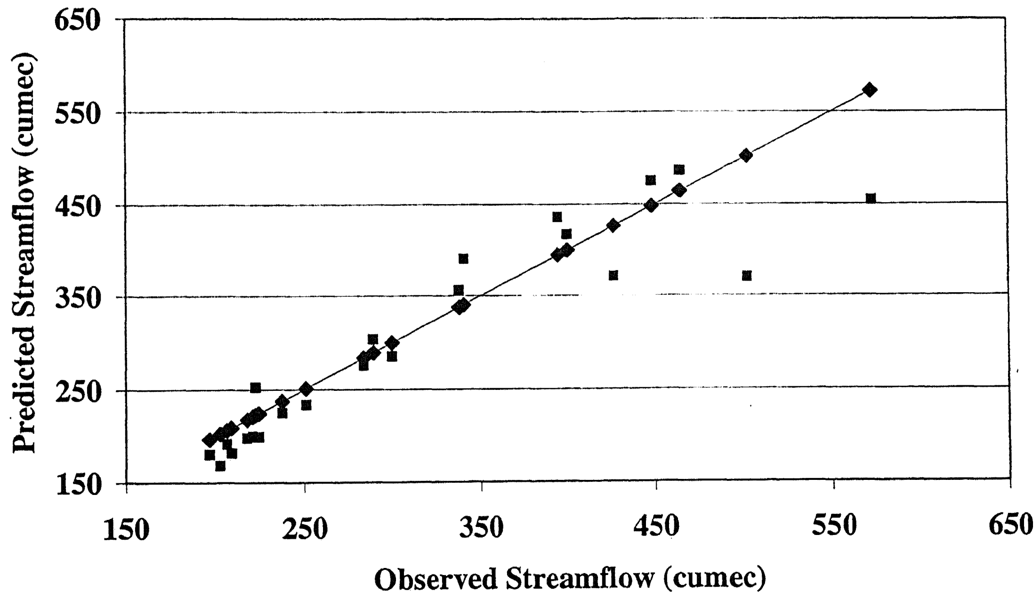


Figure B-8: Scatter Plot for Category-III storms from ANN 3-7-1 Model During Testing

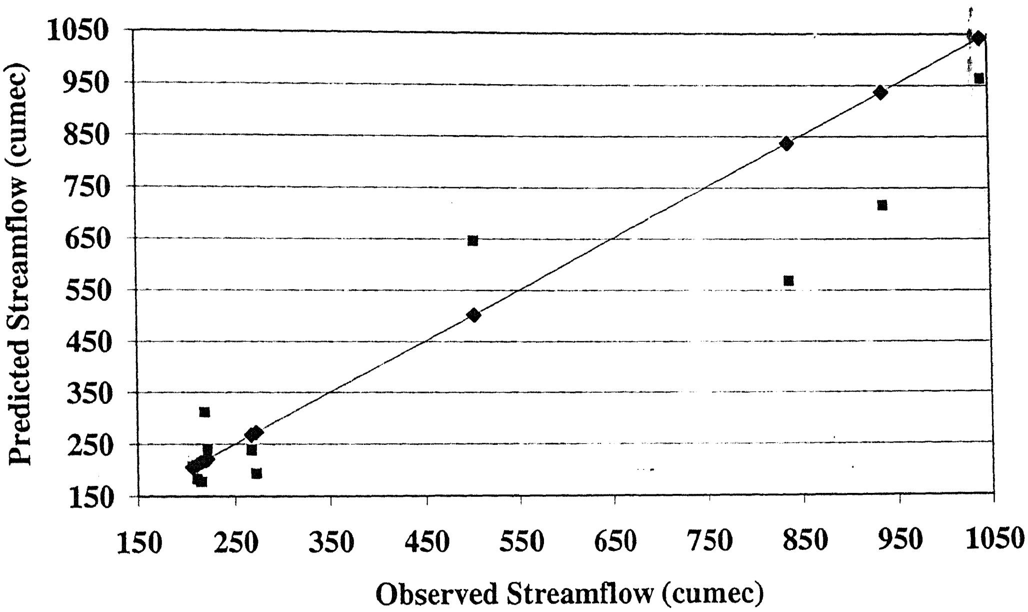


Figure B-9: Scatter Plot for Category-IV storms from ANN 2-3-1 Model During Training

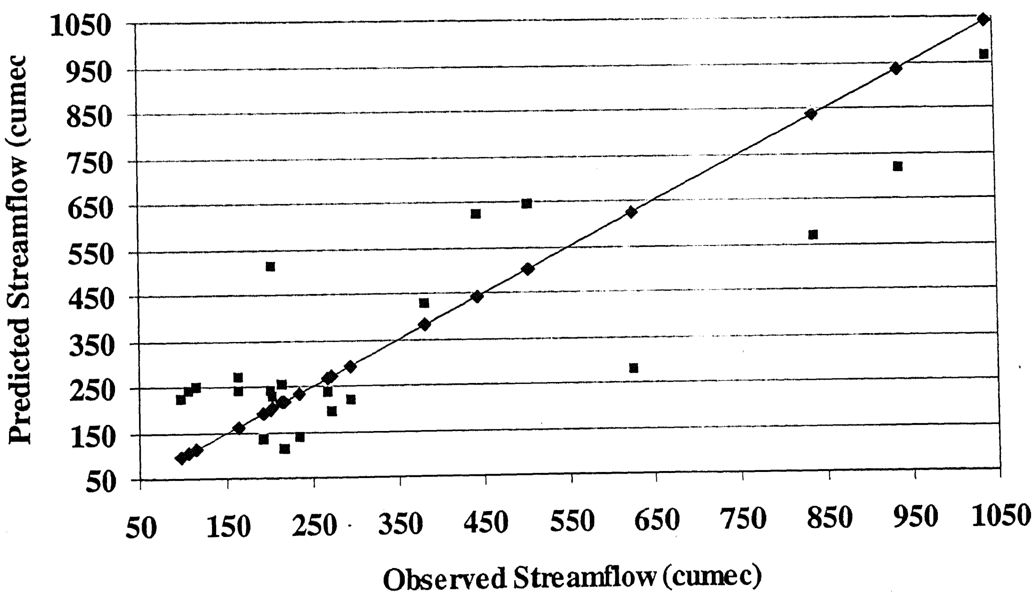


Figure B-10: Scatter Plot for Category-IV storms from ANN 2-3-1 Model During Testing

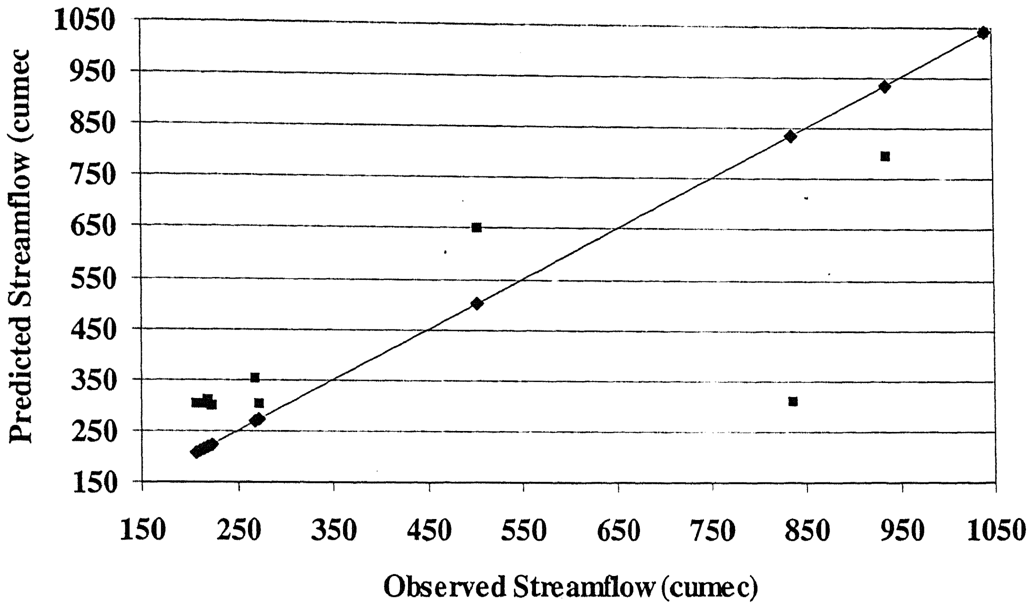


Figure B-11: Scatter Plot for Category-IV storms from ANN 2-4-1 Model During Training

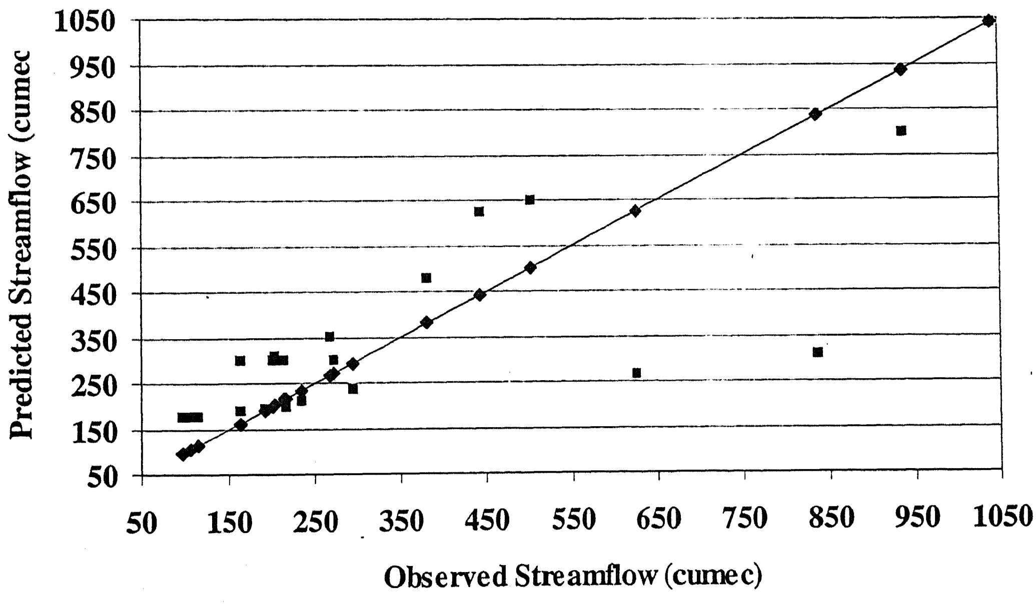


Figure B-12: Scatter Plot for Category-IV storms from ANN 2-4-1 Model During Testing

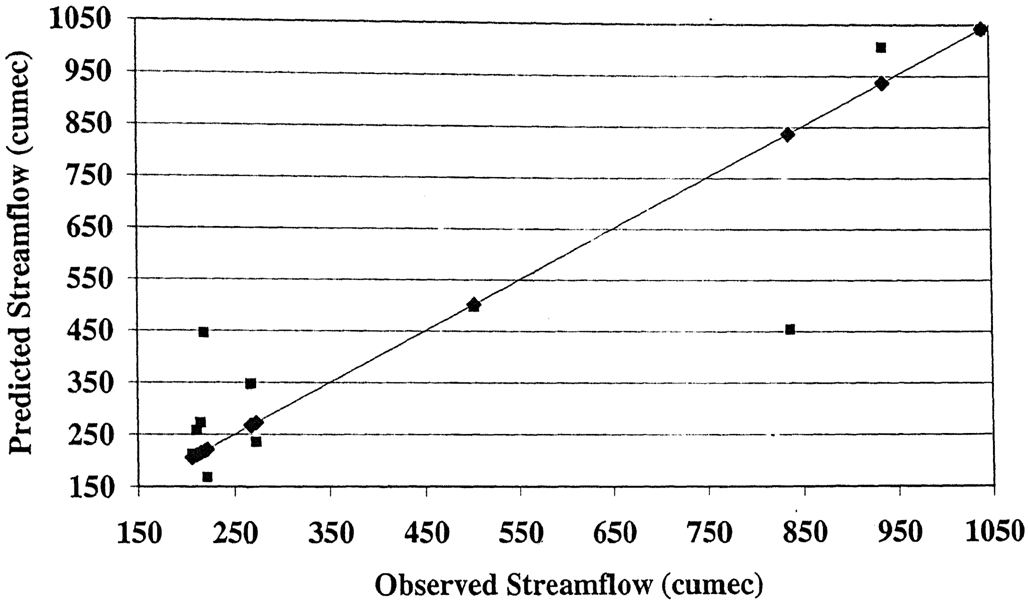


Figure B-13: Scatter Plot for Category-IV storms from ANN 3-3-1 Model During Training

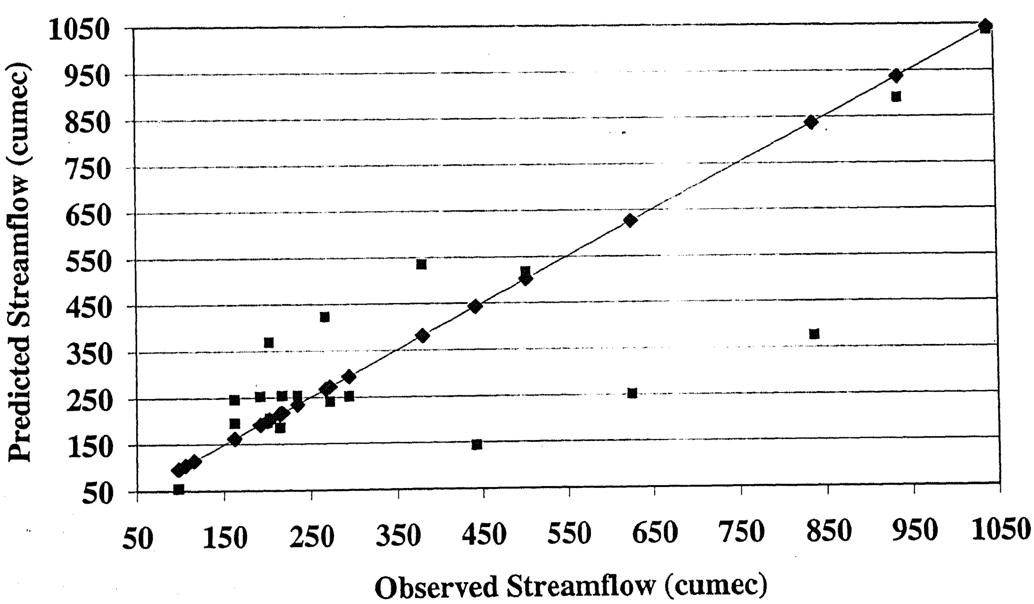


Figure B-14: Scatter Plot for Category-IV storms from ANN 3-3-1 Model During Testing

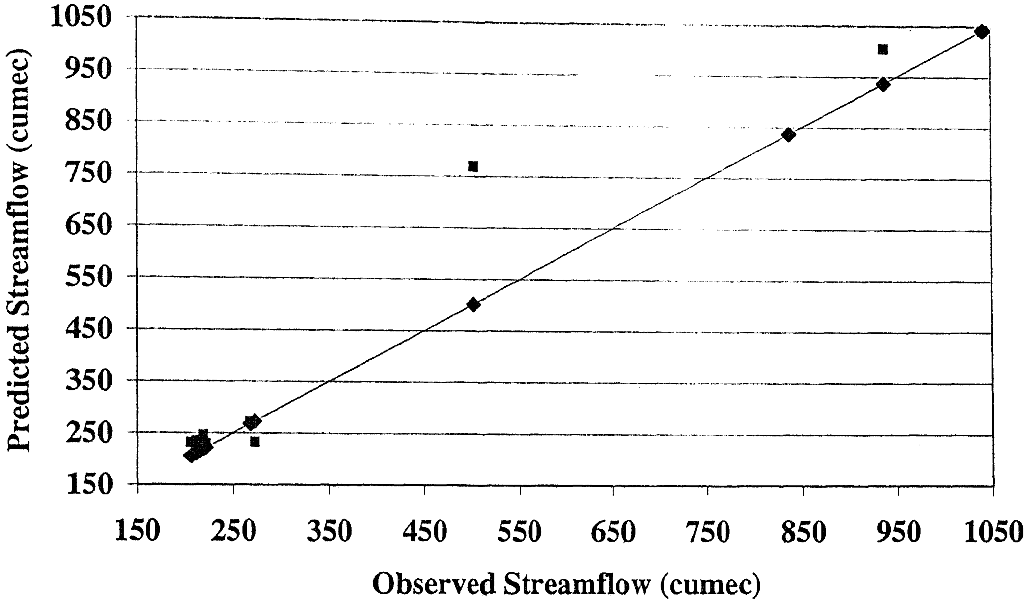


Figure B-15: Scatter Plot for Category-IV storms from ANN 3-10-1 Model During Training

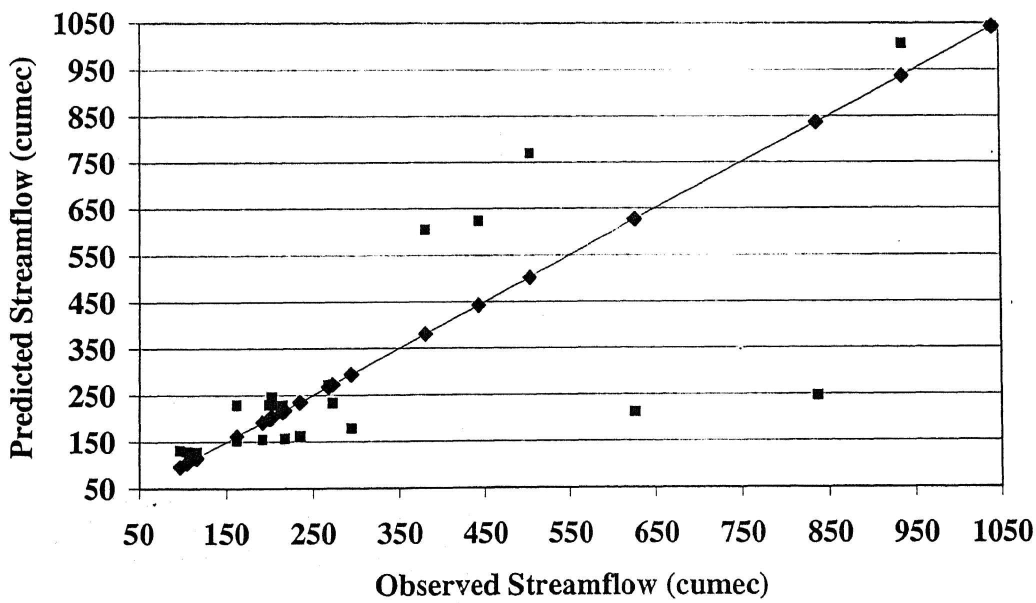


Figure B-16: Scatter Plot for Category-IV storms from ANN 3-10-1 Model During Testing

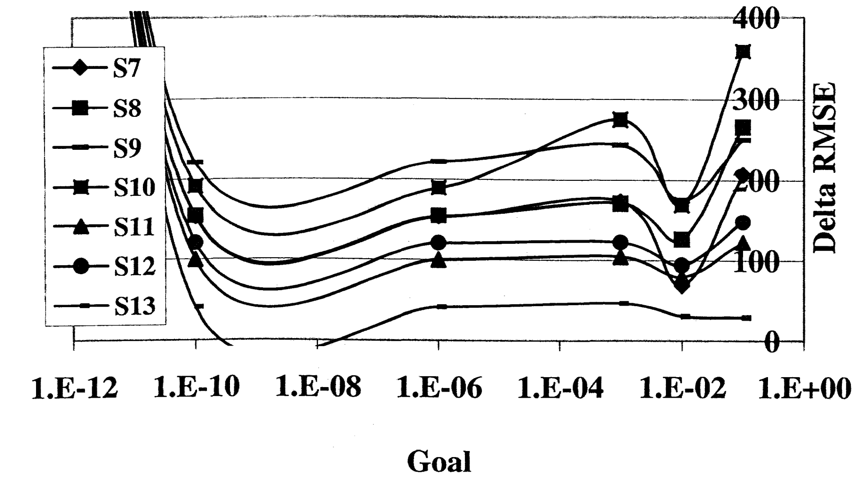


Figure B-18-1: Plot of Goal and Difference Between Training and Testing RMSE (training S6) from ANN 3-4-1 Model

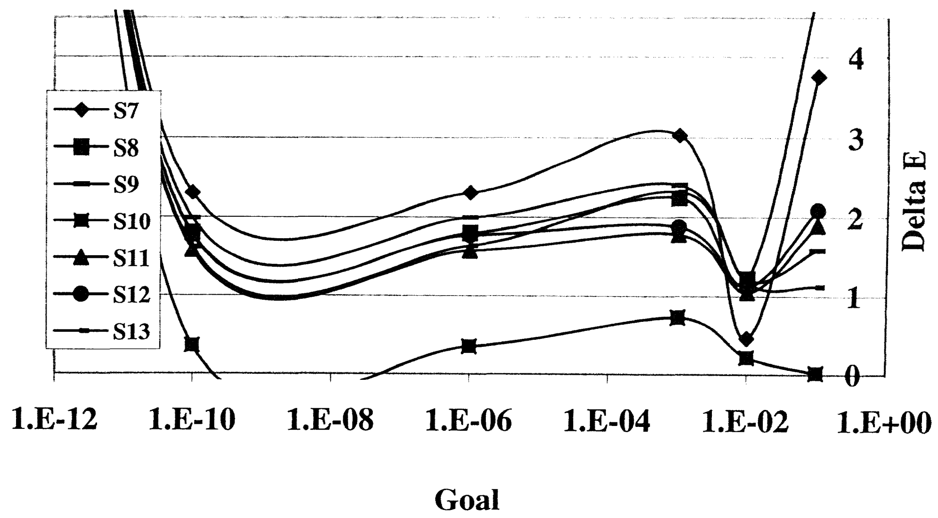


Figure B-18-3: Plot of Goal and Difference Between Training and Testing E (training S6) from ANN 3-4-1 Mode

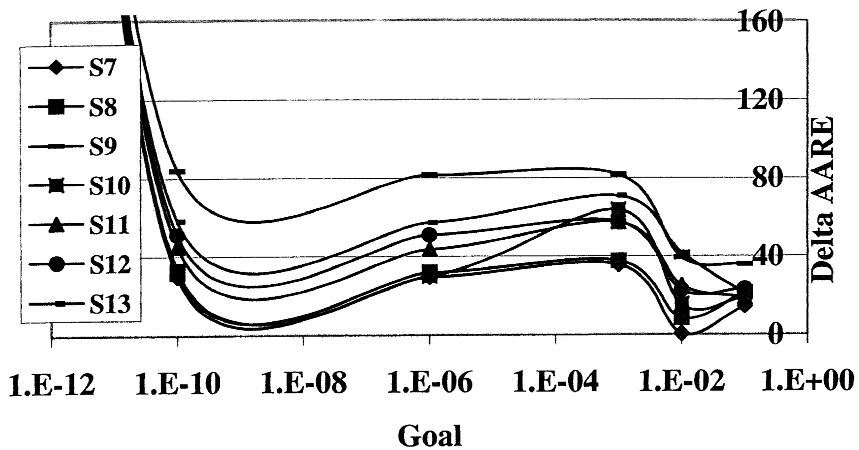


Figure B-18-2: Plot of Goal and Difference Between Training and Testing AARE (training S6) from ANN 3-4-1 Model

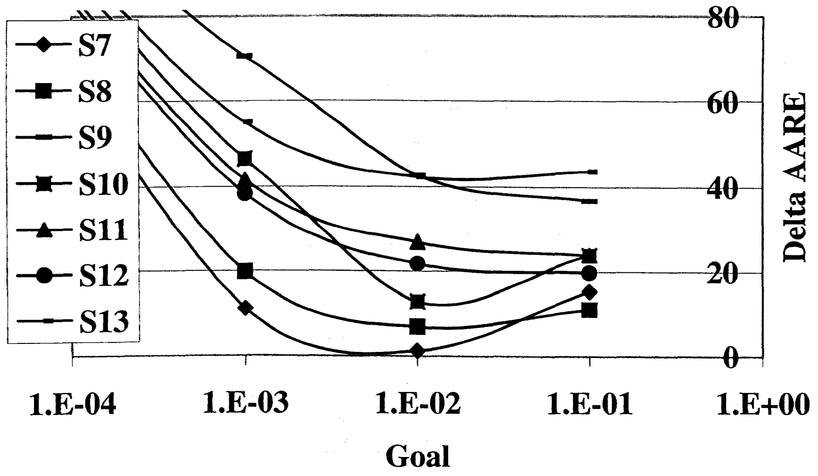


Figure B-19-1: Plot of Goal and Difference Between Training and Testing AARE (training S6) from ANN 2-3-1 Model

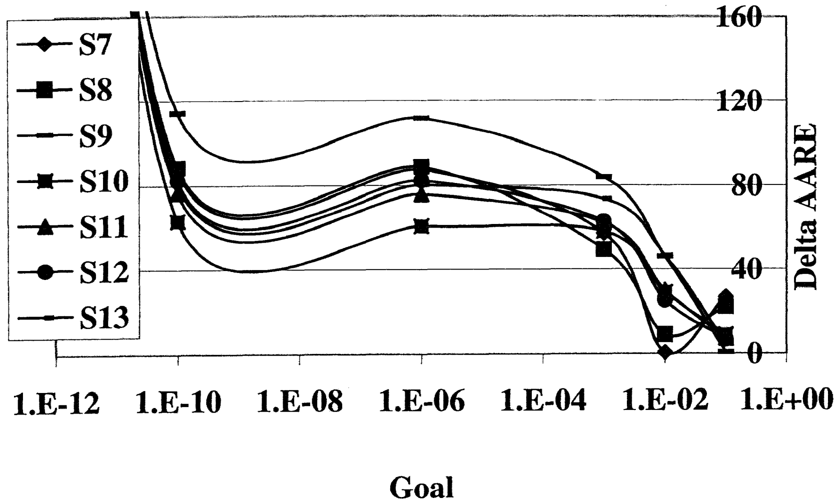


Figure B-19-2: Plot of Goal and Difference Between Training and Testing AARE (training S6) from ANN 2-3-1 Model

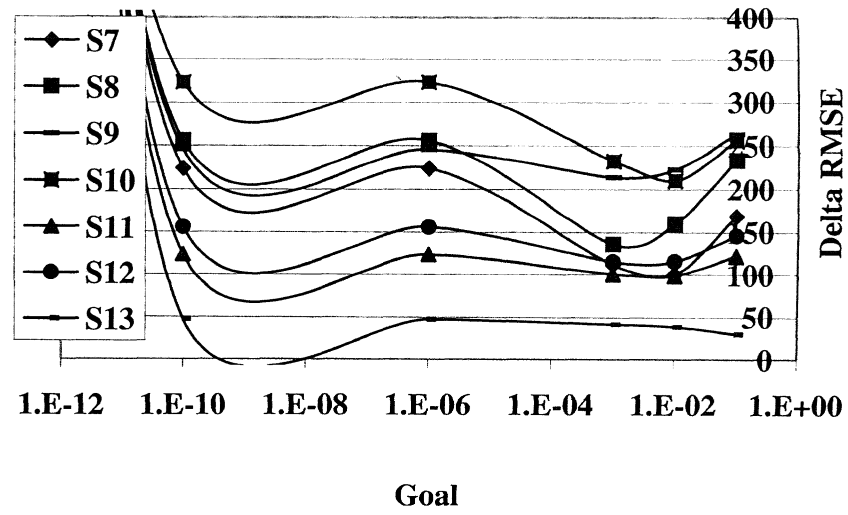


Figure B-19-3: Plot of Goal and Difference Between Training and Testing RMSE (training S6) from ANN 2-3-1 Model

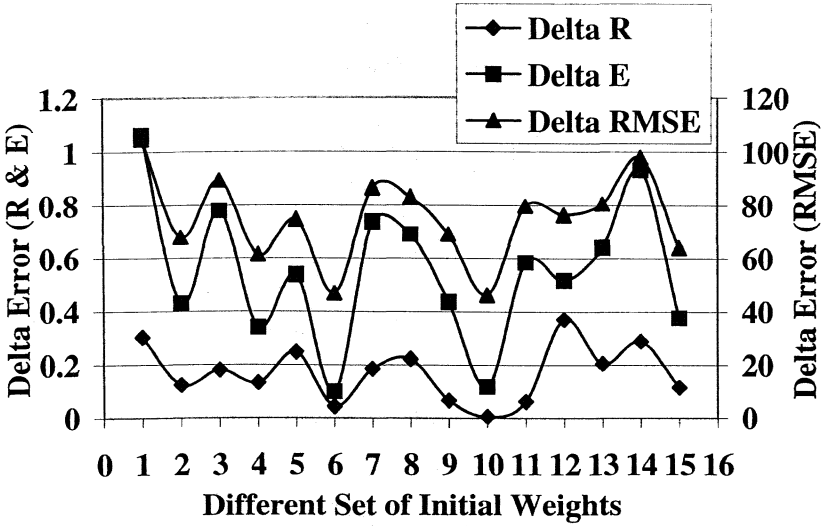


Figure B-20-1: Difference In Performance During Training And Testing For ANN 2-6-1 Model For Different Initial Set Of Weights

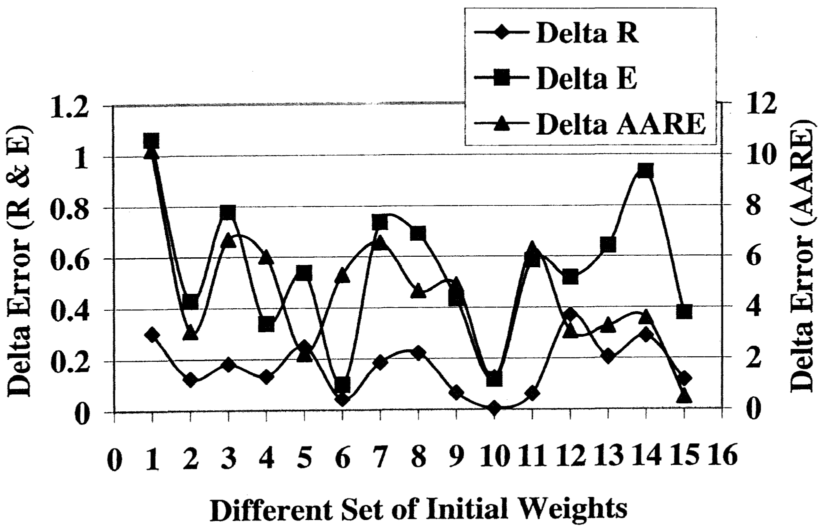


Figure B-20-2: Difference In Performance During Training And Testing For ANN 3-6-1 Model For Different Initial Set Of Weights

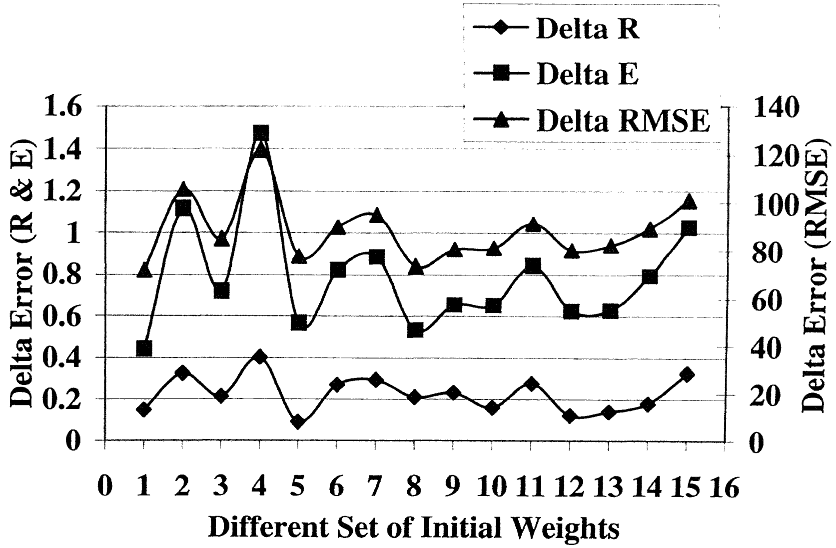


Figure B-20-3: Difference In Performance During Training And Testing For ANN 2-10-1 Model For Different Initial Set Of Weights

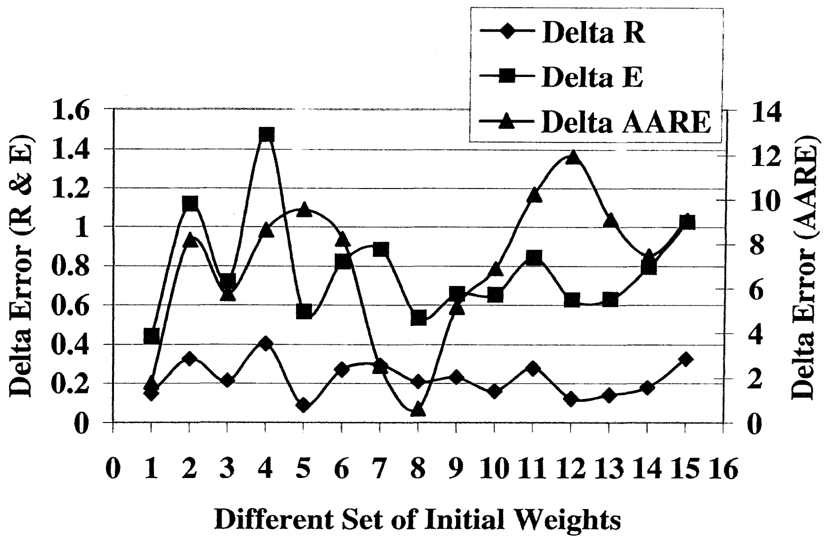


Figure B-20-4: Difference In Performance During Training And Testing For ANN 3-10-1 Model For Different Initial Set Of Weights

Table B-1: Average Rainfall, Streamflow and Effective rainfall from green-Ampt Method from all 13 Storms

	S1			S2			S3			S4			S5			S6			S13
Time (days)	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Stream flow	Effective Rainfall	Effective Rainfall
1	0	51.84	0	0	94.5	0	3.2	5.4	0	0.6	221.4	0	0	135	0	0	31.05	0	0
2	0	46.98	0	0	92.61	0	0.8	4.725	0	3.6	214.65	0	0	109.89	0	0	28.89	0	0
3	9.2	65.34	0	20.8	234.9	20.78	2	15.093	0	0	272.7	0	0	135	0	0	30.78	0	0
4	30.8	167.4	5.17	0.8	442.8	0.78	44.2	115.56	5.86	42	837	36.48	23.4	378	16.25	0	41.58	0	3.91
5	0.6	233.28	0	1	523.8	0.98	0	59.4	0	0.4	1042.2	0	0	432	0	18	85.05	1.81	0
6	0	169.56	0	0	415.8	0	0.6	25.164	0	0	936.9	0	0	310.5	0	1.2	56.16	0	0
7	0.4	125.55	0	0	324	0	0	15.093	0	0	502.2	0	0	230.85	0	0	33.75	0	0
8	0.8	96.66	0	0	275.4	0	0	11.34	0	0	267.84	0	0	184.14	0	0	26.217	0	0
9	0	81.54	0	0	233.28	0	0	9.288	0	1.8	218.7	0	1.2	155.25	0	0	22.464	0	0
10	0	70.2	0	0	182.25	0	0	8.208	0	0	210.6	0	0	137.16	0	0	21.276	0	0
11	0	61.83	0	0	153.9	0	0	6.912	0	0	205.74	0	0	122.04	0	0	19.17	0	0

	S7			S8			S9			S10			S11			S12			S13	
Time (days)	Average Rainfall	Stream flow	Effective Rainfall	Average Rainfall	Streamflow	Effective Rainfall	Average Rainfall	Streamflow	Effective Rainfall	Average Rainfall	Streamflow	Effective Rainfall	Average Rainfall	Streamflow	Effective Rainfall	Average Rainfall	Streamflow	Effective Rainfall	Average Rainfall	Stream flow
1	0	221.13	0	0.4	248.94	0	0	104.76	0	0	202.5	0	0	74.52	0	0	89.64	0	0	31.05
2	0.6	196.56	0	0	222.75	0	0.6	96.66	0	0.6	199.8	0	0	66.42	0	0	89.64	0	2.6	26.676
3	2.4	202.5	0	0.2	206.55	0	27.6	115.02	20.96	3.6	214.65	0	0	60.48	0	0	84.24	0	0.4	22.518
4	23.8	426.6	16.6	28.6	299.7	20.04	1.6	442.8	0	0	272.7	0	31.6	90.72	10.82	21.6	105.57	12.85	33.8	25.92
5	2.4	502.2	0	0	464.4	0	0	626.4	0	42	837	37.19	0	222.75	0	0	248.94	0	0	96.66
6	0	399.6	0	4.2	572.4	0	0	380.7	0	0.4	1042.2	0	0	326.7	0	0	380.7	0	0	124.74
7	0	340.2	0	0	448.2	0	0	294.3	0	0	936.9	0	0	226.8	0	0	278.1	0	0	65.34
8	0	288.9	0	0.2	394.2	0	0.4	234.9	0	0	502.2	0	2.2	170.64	0	0	210.6	0	0	40.5
9	1.8	251.1	0	0.4	337.5	0	1.2	217.08	0	0	267.84	0	2.2	147.15	0	0	164.16	0	1.4	33.48
10	0.6	224.37	0	0	283.5	0	8.4	191.7	1.76	1.8	202.5	0	0	128.25	0	0	137.16	0	0	31.86
11	0	208.98	0	0	237.6	0	0	162	0	0	162	0	1	101.52	0	2.4	112.32	0	0.4	28.89

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